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The Effect on Electricity Consumption of the Commonwealth Edison Customer Application Program Pilot: Phase 1, Appendices

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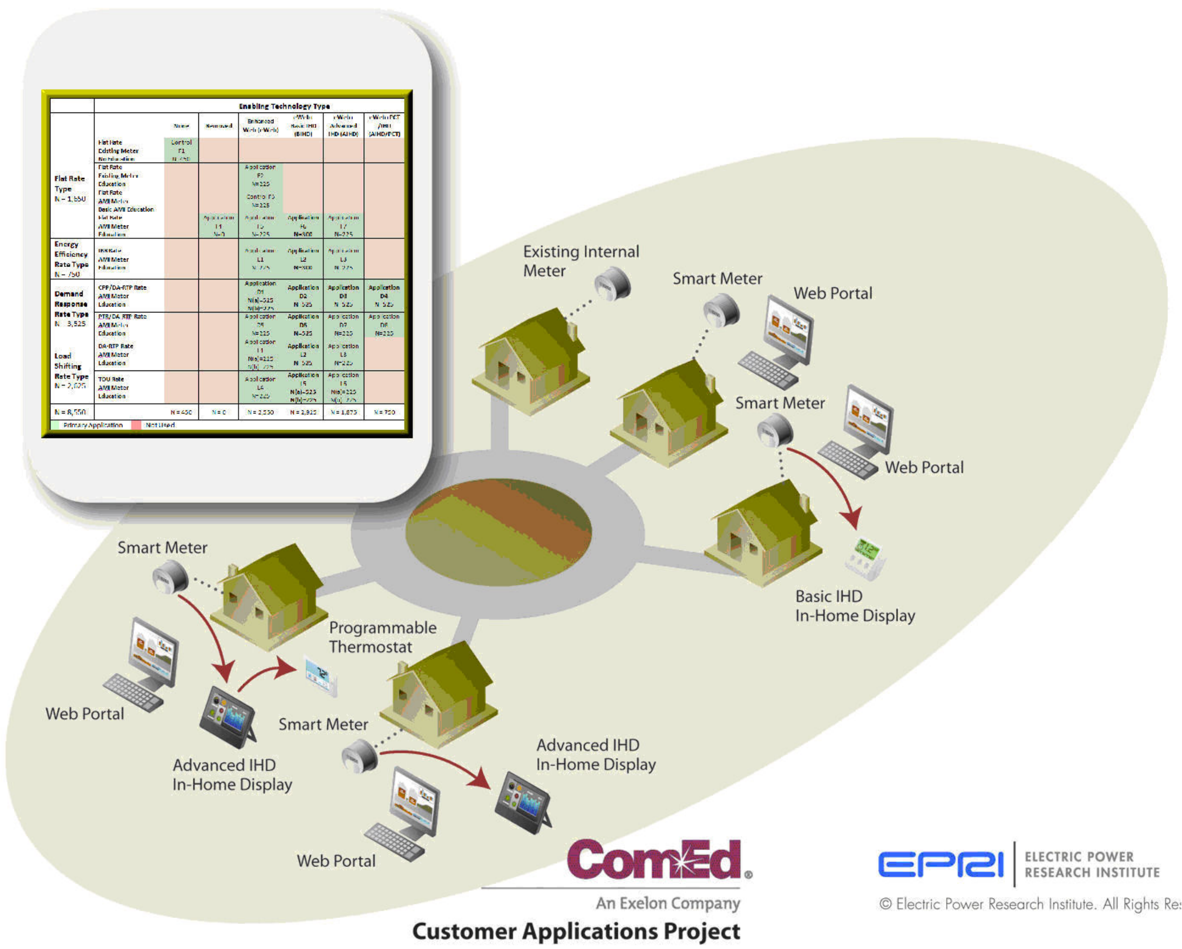

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Technical Update, April 2011

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PRODUCT DESCRIPTION

This report provides appendices that support Electric Power Research Institute (EPRI) report 1022703, which describes the Phase 1 analysis of some aspects of residential customers' response to Commonwealth Edison's Customer Application Plan (CAP). This report contains technical materials that describe in detail all of the methods employed in conducting the Phase 1 analysis and presents the results of the application of those methods.

Results and Findings

The main purpose of the analysis described in these appendices and the associated report is to determine the extent to which residential customers' consumption of electricity is affected by various combinations of innovative rate design and smart grid enabling technologies. This report serves as a technical document that supports the Phase 1 analyses reported in 1022703. It describes the model and methods used to test the hypotheses (detailed in EPRI report 1022266) that were established to guide the development and evaluation of the CAP.

Challenges and Objectives

Demand response is becoming increasingly important as an adaptation to the rising costs of building new generation plants, siting new transmission and distribution facilities, and dealing with a variety of environmental issues, notably including climate change. Improvements in communications and controls reduce costs and extend the range of potentially responsive loads. Many regulators are pressing utilities to fully use a range of demand response solutions. An analysis of the efficacy of smart grid technologies in facilitating demand response is essential to determining the ways in which these technologies should be used.

Applications, Value, and Use

The wide range of issues addressed in the CAP required the use of several methods to test hypotheses and produce data that characterize how customers responded to the applications that were administered. The Phase 1 analysis, which was conducted in late fall 2010, used meter data and other CAP program data for the months of June through August 2010. Because that period was designed for implementing high prices for critical peak pricing (CPP), peak time rebate (PTR), and real-time pricing (RTP), it focused on quantifying impacts for these three dynamic rate options. Accordingly, the most relevant elements of this report are those that discuss how CAP participants reacted to those prices and the corresponding results of their applications. Additional applications were also tested, but the results are preliminary because the information and technology treatments required to analyze them will not be complete until the end of the CAP experiment.

EPRI Perspective

This report addresses an important part of determining how the smart grid can best facilitate demand response. It is part of a series of studies contributed by EPRI to help the power industry exploit technological advances to increase reliability and reduce costs while adapting to increased environmental constraints on the ways that the industry provides its services to customers.

Approach

This report describes the methods by which EPRI researchers are evaluating the efficacy of smart grid technologies in providing demand response to Commonwealth Edison and provides the first set of results from this evaluation.

Keywords

Advanced metering infrastructure (AMI)
Alternative electricity price structures
Critical peak pricing
Enabling technology
Inclining block rate
Peak-time rebates
Opt-in and opt-out
Real-time pricing
Time-based pricing

ABSTRACT

This report provides appendices that support Electric Power Research Institute (EPRI) report 1022703, which describes the Phase 1 analysis of some aspects of residential customers' response to Commonwealth Edison's (ComEd's) Customer Application Plan (CAP). The objective of the evaluation is to determine the effects on customers' energy consumption patterns of various rate treatments, behavioral factors, and enabling technology applications. Many of the anticipated CAP effects are addressed in a series of hypotheses, derived from the CAP design, regarding the effects of the various rate, technology, and education treatments featured in the pilot. These interim findings constitute Phase 1 of the evaluation, and they are based on an analysis of data for the first three months of the CAP pilot (June–August 2010). The findings support some, but not all, of the hypotheses. Phase 2 of the analysis will be completed in fall 2011 and will contain an extension and update of the Phase 1 analysis. It will be based on participants' electricity consumption and price data for the entire year of the CAP pilot as well as data collected through a survey of CAP participants. When this Phase 2 analysis is complete, it should be possible to expand the results of the CAP pilot to the ComEd residential population.

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A
CUSTOMER DEMAND MODELING

This appendix develops several demand models needed to predict electricity usage under the five alternative rate structures that comprise the CAP pilot. We begin with a general non-technical discussion of how best to view demand for electricity as only one of a large number of commodities purchased by residential utility customers. This view facilitates a graphical depiction of how electricity purchases are allocated among different time periods, separate from the allocation of total income among all purchases. While this distinction adds transparency to the analysis, it is driven in part by the nature of the data that are typically available from pilot studies on the impact of alternative rate structures. The components of this framework can be used to inform the necessary mathematical demand models needed for several of the intended CAP analyses and how they must differ to deal with the five rate structures. We discuss the strengths and weaknesses of each specific functional form of the demand models. Finally, we discuss several technical issues regarding empirical specification and econometric estimation.

Conceptual Models for Electricity Demand

The methodologies for estimating the effects on electricity usage of alternative electricity rate structures and enabling technologies are based on the neoclassical theory of customer behavior. As suggested by Caves and Christensen (1980b,c) and others in their analyses of early electricity pricing experiments, such an approach ensures that the empirical specification of the estimated demand equations is consistent with the maximization of customer utility (*e.g.*, satisfaction) subject to a budget constraint, and that the estimated demand elasticities are internally consistent.

Further, by placing certain restrictions on the form of the utility function, it is possible to conceptualize the analysis in stages. This is important for several reasons. Residential customers purchase electricity along with a large number of commodities, including other types of energy and products such as housing, transportation, clothing, food, health care, education, and recreation. Within each of the major categories, expenditures are allocated among the subcomponents of each category - for example, among meat, vegetables, and grains in the food category.

However, as a commodity, electricity is unlike most others. Since it is not storable, it is generally purchased continuously throughout the day on an as-needed basis. Equally important, electricity is not consumed directly by customers. Rather, its demand is a derived demand since customers derive satisfaction (*e.g.*, utility) from the services that come from electrical appliances. Thus, the satisfaction from purchases of electricity is embodied in the derived demand for distinct services such as lighting, HVAC, electronic devices, ovens, refrigerators, etc. In the short run, a utility customer's demand for electricity is conditioned by an existing stock of electrical appliances. As suggested by much of the research into the value of feedback information, the demand for electricity may well be further conditioned by the availability of Advanced Metering Infrastructure (AMI) technology and education (*e.g.*, Boisvert, *et al*. 2009).

By viewing the analysis of electricity demand in stages, we can distinguish at a minimum between a customer's allocation of electricity purchases among different time periods from the allocation of total income or expenditures between electricity and other non-durable goods and services in any time period. Beyond the transparency it brings to the analysis, Caves and Christensen (1980b) argue that it is desirable, if not essential, to analyze the allocation of electricity expenditures in stages because of the availability of data. As in other experiments with time-differentiated electricity rates, the pilot involving the five rate treatments in ComEd's CAP provides extensive data on electricity use and rates, some data on structure characteristics and appliance stock, but very little, if any, information on the purchase of other goods. At best, there is likely to be only crude estimates of income. By focusing exclusively on electricity use while disregarding income and the customer's total budget, we can make good use of the detailed data from the pilot; but in so doing, the estimates of the important demand elasticities are only partial elasticities.

As is explained in more detail below, implicit in this two-stage analysis is the assumption that electricity is separable in the customer's utility function.[1] Accordingly, the customer's budgeting process can be viewed as proceeding in two stages. Our focus is therefore on the first stage of the process in which we can characterize the allocation of electricity use by time-of-day. While the elasticities from this stage are partial elasticities of substitution and partial price elasticities, they have a number of useful interpretations that are also discussed below.[2]

Conditional Demand for Electricity

In modeling the customer's allocation of daily electricity for the CAP rate treatments that differ by hour, it would be possible conceptually to model each hour of the day. For purposes of discussing the modeling framework, however, it is sufficient to examine the allocation of

---

[1] The critical assumption underlying the separability of consumption is that an individual's preference between two collections of goods that differ only in the components of one subset of a category are independent of the identical other components of another category in the two consumption baskets. In addition to its intuitive appeal, this assumption of separability allows for the identification of conditional demand functions for goods in any category. These conditional demand functions can be defined for when one or more goods is pre-allocated. In general, a conditional demand function for a good in the remaining subset that is not pre-allocated expresses the demand for that good, as a function of: 1) the prices of all goods in the subset of goods not pre-allocated; 2) total expenditures on the subset of goods; and 3) the quantities of pre-allocated goods (*e.g.*, Pollak 1971, p. 424).

[2] The primary focus of empirical analysis of the demand for electricity is on estimating the elasticity of substitution between peak and off-peak electricity demand, and how this differs for customers across rate treatments. This elasticity of substitution is often denoted by σ, and in our case it measures the substitution effect that is quantified by the percentage change in the ratio of peak to off-peak electricity use caused by a one percent change in the ratio of off-peak to peak electricity prices. In conducting the empirical analysis, we do, however, also obtain estimates of the conditional own-price elasticities of demand for peak and off-peak electricity. These are defined as the percentage changes in peak (off-peak) electricity use caused by a one percent change in the price of peak (off-peak) electricity. These own-price elasticities are estimated primarily to check that the estimated models are consistent with demand theory. They do offer some measure of demand response in a particular time period to changes in the price in that period, but they must be interpreted with care. Since we have no data on customers' income, our estimated own-price elasticities of demand for peak and off-peak elasticity are measured conditional on the level of a customer's utility remaining unchanged.

electricity consumption between high-priced (peak) hours and low-priced (off-peak) hours. [3] This issue is addressed in detail below.

Since this modeling framework measures the amount of load shifted from peak to off-peak periods, it is particularly appropriate for the analysis of rates that differ by time of day, regardless of whether the rate involves fixed time-of-use (TOU) rates or rates that have a dynamic aspect like day-ahead real-time pricing (DA-RTP) or critical peak pricing (CPP). The model may also offer limited information about overall energy conservation.

In contrast, this model of the first-stage decision process is not sufficient to examine rates such as an inclining block rate (IBR) since prices under this rate do not vary by time of day. The price varies by the quantity consumed. The primary decision of customers under the IBR rate involves how much electricity to consume during the billing period rather than how much electricity to consume at different hours of the day. Through its inclining block, the IBR rate embodies an incentive to reduce overall electricity consumption; and the critical part of the customer's choice is the selection of the block within which to consume the last unit of electricity. The framework necessary to study customer price response under an IBR rate is discussed separately below.

Modeling Customer Response to Prices that Differ by Time of Day

Electricity uses in two distinct daily periods (*e.g.*, peak and off-peak) may be valued differently by the customer. It may also be the case that peak and off-peak electricity consumption are complementary goods so that the customer demands electricity in the two periods in nearly fixed proportions (e.g. Taylor, *et al*. 2005 and Boisvert, *et al*. 2007). To capture these ideas in a demand model, we specify a customer's utility function that is separable in electricity commodities as:

$$(1) \qquad V \quad = \quad V\left(x_1, x_2, ..., x_n, U\left(k_p, k_o\right)\right)$$

where V is utility function of the customer, x_i are the goods and services other than electricity consumed, and k_p and k_o are the amounts of electricity consumed in peak and off-peak periods, respectively. Electricity is assumed to be separable in consumption from other goods and services. Therefore, the sub-function $U(k_p,k_o)$ represents a sub-utility function for the customer; it reflects the fact that a customer can attain a given level of satisfaction from electricity consumption by consuming different amounts of peak and off-peak electricity that together yield a given level utility or satisfaction, say U_0.

In considering the use of peak and off-peak electricity, there are three cases that should be distinguished. The particular case that applies to any individual customer depends on individual tastes and preferences, conditioned in part by its stock of electrical appliances. These three cases

[3] The use of the terms "peak" and "off-peak" are primarily for convenience and are used to distinguish between those hours in which prices are generally high and those when they are low. This division of hours may or may not correspond with the system peak.

are described graphically here.[4] In later sections, the individual cases are related directly to the estimated parameters of the Generalized Leontief (GL) demand models, which we propose to use for quantifying the price impacts of CAP rate plans.

Case 1, depicted in Figure A-1, is where peak and off-peak electricity are substitute goods in consumption. This case is what most would think of as the normal situation that portrays a customer's substituting peak and off-peak electricity at some rate and still remaining equally satisfied.

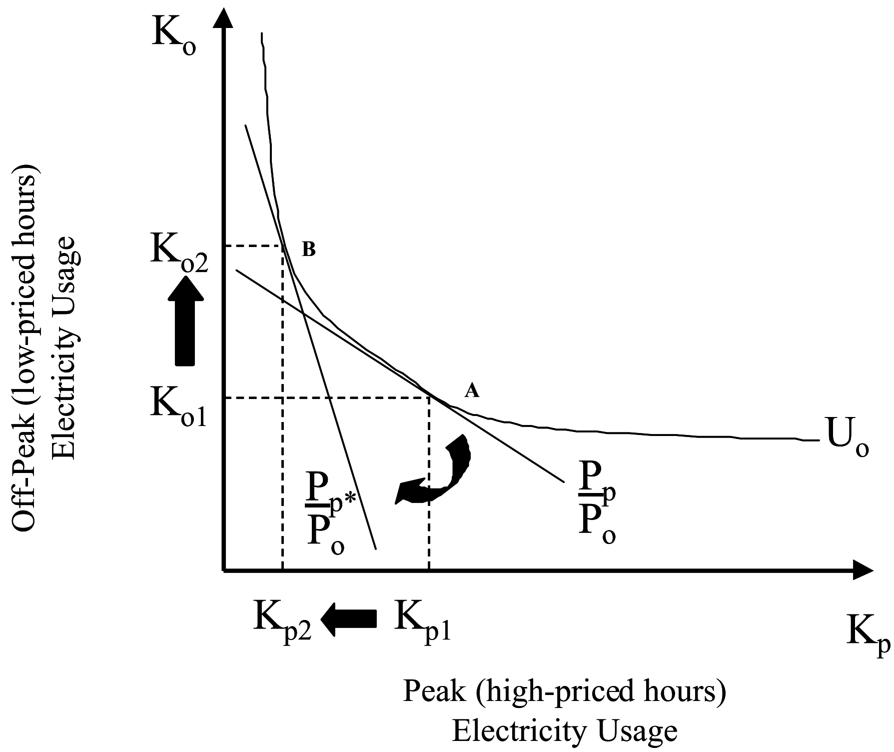

Figure A-1
Peak and Off-Peak Electricity as Substitute Goods

The curve U_o in Figure A-1 represents those combinations of peak electricity (K_p) and off-peak electricity (K_o) that leave the customer equally well off (*i.e.*, at the same utility level). At an initial ratio of peak (P_p) to off-peak (P_o) electricity prices, the price line labeled P_p/P_o represents all combinations of K_p and K_o that the customer can purchase for a fixed budget. Given this budget constraint, a customer in turn would maximize his/her utility by consuming K_{p1} and K_{o1} of peak and off-peak electricity, respectively. This is point A in Figure A-1. Any other combination of peak and off-peak usage would lower the overall level of utility realized.

If there is an increase in the peak period price of electricity to $P_p^* > P_p$, the price line gets steeper; and if the customer wants to maintain the same level of utility, U_o, he/she would do so by using

[4] These three cases were originally discussed by Diewert (1971) in the context of a firm's derived demand for productive inputs.

more electricity off peak and less on peak (*e.g.*, $K_{p2} < K_{p1}$ and $K_{o2} > K_{o1}$). This is at point B. It is the increase in the peak price of electricity that leads to a decrease in the ratio of peak to off-peak electricity usage.

It is this change in the ratio of peak to off-peak electricity use that measures the customer's price responsiveness. This change in consumption intensity is related to the slope of the curve, U_o. The measure of this change in the ratio of electricity use in percentage terms is commonly called the elasticity of substitution, and it is often denoted by σ. In our case, σ measures the substitution effect that is quantified by the percentage change in the ratio of peak to off-peak electricity use caused by a 1% change in the ratio of off-peak to peak electricity prices. As the curvature or slope of U_o becomes more pronounced, a customer's price responsiveness, as measured by the elasticity of substitution falls, and as the curve U_o becomes flatter, the price responsiveness increases. Finally, in this particular case, we have drawn the curve U_o so that it never crosses either axis. Thus, regardless of how high the peak price rises relative to the off-peak price, the customer will always consume some peak electricity as part of any equilibrium level of satisfaction. Technically, this is the case where $0 < \sigma < \infty$.

Case 2 is depicted in Figure A-2. It is an extreme case, where $\sigma = 0$, but, it may be of particular interest in the study of residential customer price response. In this case, there is no possibility for substituting peak for off-peak electricity regardless of the relative prices of peak and off-peak electricity. This means that for a customer to maintain a level of utility equal to U_o, electricity in the two periods must be consumed in fixed proportions, and peak and off-peak electricity are called perfect complements. The equal utility curve, U_o, is the rectangle in Figure A-2, and it can be attained only by consuming K_{p1} and K_{o1} units of peak and off-peak electricity, respectively.

The fixed proportions nature of consumption is reflected in the rectangular curve characterization of U_o in the following way. If K_p is increased above the level K_{p1} while holding K_o at K_{o1}, we would move to the right horizontally along the curve U_o. Since we remain on the curve U_o, the customer's utility level remains constant, and the extra peak electricity yields no increase in satisfaction to the customer. A similar argument can be made for trying to increase the customer's utility by increasing the amount of off-peak electricity without any increase in peak usage.

Case 3 is depicted in Figure A-3. It is discussed primarily for completeness, as it was found to be important in a similar study of commercial and industrial customers (Boisvert, *et al*. 2007). The extent to which it applies to residential customers is of course an empirical question. As in Case 1 above, peak and off-peak electricity are substitute commodities. Points on curve U_o represent those combinations of peak electricity (K_p) and off-peak electricity (K_o) that yield a utility level of U_o. At an initial ratio of peak to off-peak electricity prices (given by the price line in Figure A-3 labeled P_p/P_o), the customer would maximize utility U_o for the implied budget expenditure by consuming K_{p1} and K_{o1} of peak and off-peak electricity, respectively. This is point A in Figure A-3. In contrast to the situation in Figure A-1, however, we see that in this case the V_o curve cuts the vertical axis at point B. Although off-peak electricity is substituted for peak electricity as the price of peak electricity rises, there is a price (say P_p^*), at which peak electricity is "priced out of the market", and peak usage drops to zero (point B in Figure A-3).[5]

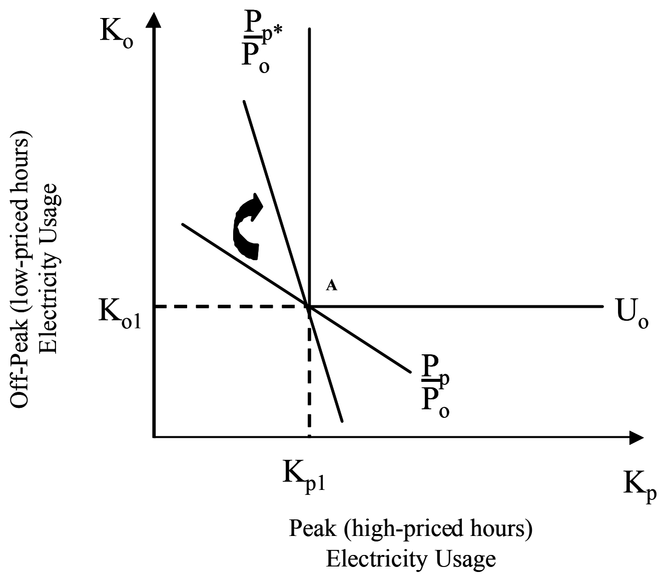

Figure A-2
Peak and Off-Peak Electricity are Perfect Complements

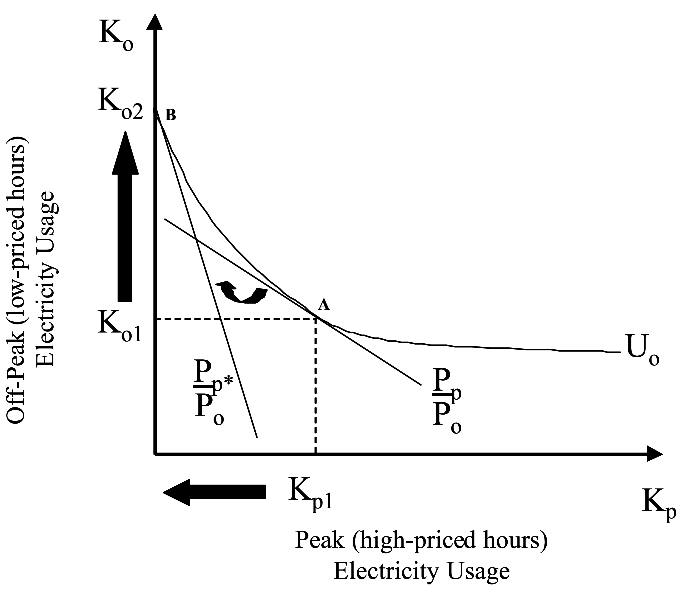

Figure A-3
Peak and Off-Peak Electricity are Substitutes – Peak Usage is "Priced Out"

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[5] In the study described in Boisvert *et al*. (2007), a small number of firms have production processes that accommodate such dramatic substitution possibilities and enable forgoing all electricity use during peak periods when peak prices are extremely high. Such firms may have significant on-site generation: although they require peak electricity as an input, their demand for peak power from the *grid* can fall to zero (point B in Figure A-3) as the price of peak electricity rises to a certain level and they rely completely on their own generation.

Modeling Customer Response to an Inclining Block Rate

In contrast to the other rate treatments in the CAP pilot, where prices differ by time of day, the prices in an inclining block rate (IBR) differ depending on the amount consumed during a billing cycle. IBR rate designs generally have prices that increase as the customer's load increases, with constant prices within each kWh block. The CAP IBR involves an additional feature: the IBR rate has increasing prices for the first three blocks, followed by a substantial (50%) drop in price for the final block, so that subsequent usage is priced at close to the standard ComEd residential tariff. This feature of the rate design leads to some modeling issues that are discussed below.

The logic of how to model electricity demand under an IBR rate can be articulated effectively, and without loss of generality, using a two-block example. This rate design, along with a comparison with a flat rate, is depicted in Figure A-4.

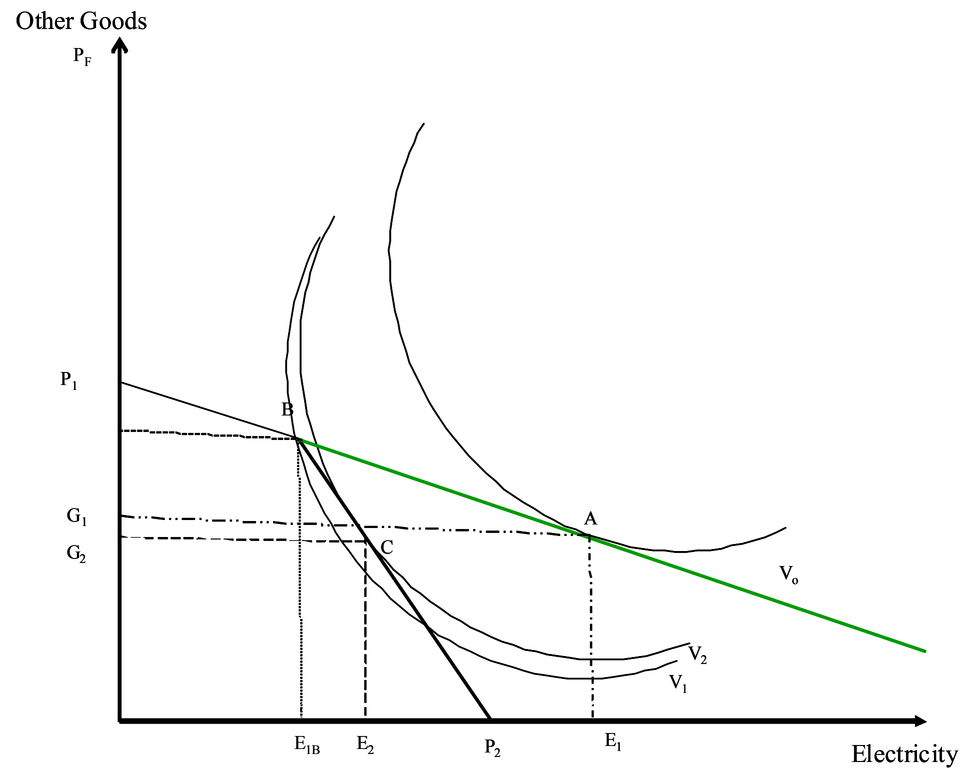

Figure A-4
Residential Demand Response to an Inclining Block Rate (convex budget constraint)

Figure A-4 depicts a model that focuses on the second (rather than the first) stage of the decision process described above. That is, rather than distinguishing between a customer's allocation of electricity purchases among different times of the day, Figure A-4 depicts the allocation of total income or expenditures between electricity and other non-durable goods and services. The quantities of electricity purchased are on the horizontal axis, while purchases of other goods are measured on the vertical axis. Each indifference curve (V_i) represents all combination of electricity and other goods that leave the customer's utility (level of satisfaction) at a constant level. As before, a budget constraint determines where utility is optimized.

It is convenient to begin the analysis at point A, which is where the customer would maximize utility (V_o) from the purchase of electricity and other goods. The customer's purchases are subject to a budget constraint whose slope reflects a low price of electricity (could be the flat rate) so that the customer could make purchases anywhere along the line P_1-B-A and beyond. With this constraint, the customer maximizes utility at V_o, where the indifference curve is tangent to the budget line. At this initial equilibrium, the customer purchases E_1 units of electricity and G_1 units of other goods.

This situation is changed substantially by the move to an inclining block electricity rate. If the first block of electricity can be still be purchased at the same price, then for purchases of electricity between $0 \leq E \leq E_{1B}$, the customer can purchase anywhere along the line P_1 – B. However, if the price of electricity is increased for purchases above E_{1B}, the price per unit would be higher, and for the customer to purchase more electricity, he/she would have to move down a portion of the new budget constraint B-P_2. The budget constraint now has a kink in it. The new equilibrium point would be at point C, with purchases of electricity E_2, less than E_1, the quantity that would be purchased if the rate for the first block applied to all electricity purchases. The quantity of other goods would likewise fall from G_1 to G_2.

While the logic of this geometric depiction of the effects of an increasing block rate is rather straightforward, the mathematical and econometric modeling of this situation is not. In the case where only the lower rate applies, the equilibrium is where the indifference curve is tangent to the budget line. However, in the case of the inclining block rate, the end point of the budget constraint for the first block does not occur at a tangency with an indifference curve, although it is nonetheless readily identifiable as the upper block boundary. Furthermore, the point is also a part of the utility maximization of the second block where the interior solution at point C (a tangency between the budget line and the indifference curve) has a higher utility, V_2. Since this a conditional maximum (conditioned by choosing to consume in the second block), the second block must be modeled as a discrete choice (e.g. Reiss and White 2005 and Hewitt and Hanemann 1995).

The modeling situation for the CAP IBR is further complicated by the fact that electricity beyond the limits of the last block can be purchased at a price below the price in the final block. This situation is depicted in Figure A-5. This figure differs from Figure A-4 only in that there is a third block for electricity purchases. Amounts of electricity above E_{2B} can be purchased at a rate lower than for the second block. Consequently, the budget constraint has a second kink in it, but it is one in which the constraint becomes less steep. Mathematically, this forms a non-convex budget constraint, and this leads to further complications in modeling. This complication is illustrated by examining points C and F. Both are interior solutions (points of tangency between an indifference curve and the budget line), but we now have a situation in which there are two discrete choices that cannot be identified uniquely since each leads to the same level of customer utility (e.g. Strong and Smith 2010). In contrast, had the rate for this third block been higher than for the second, the discrete choices between the final two blocks would have led to different levels of utility, and thus could be modeled as well-defined, distinct discrete choices.

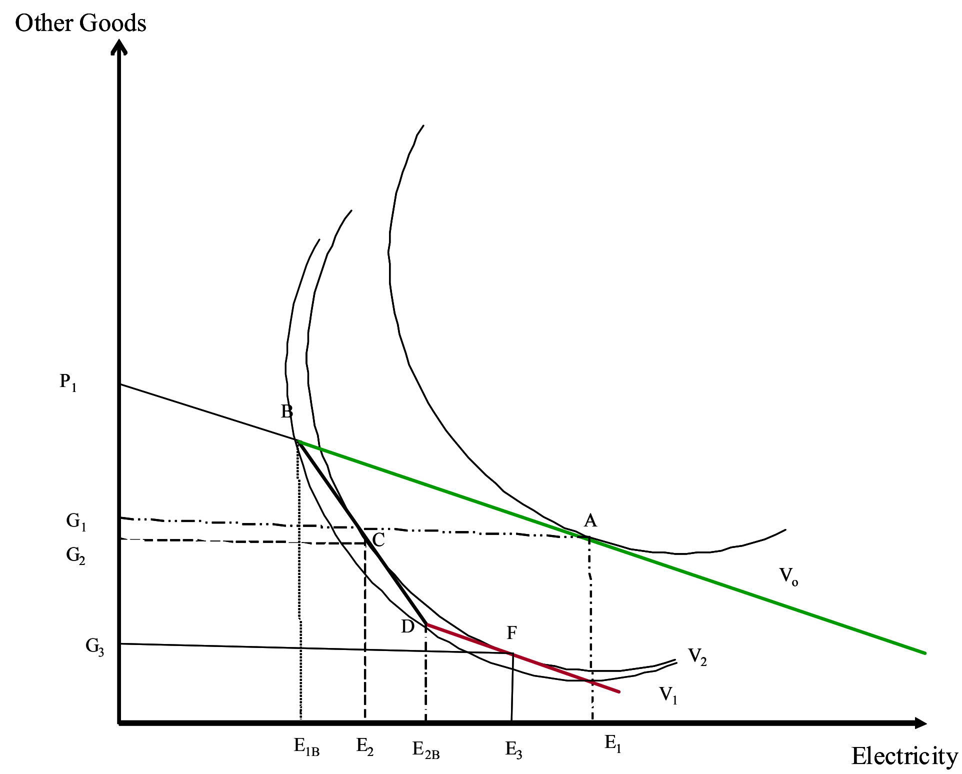

Figure A-5
Residential Demand Response to an Inclining Block Rate (non-convex budget constraint)

Since the analysis of the inclining block rate must consider the total demand for electricity rather than demand by time of day, the issues involved in modeling can also be underscored using two conventional demand diagrams, such as those in Figure A-6 and Figure A-7. In each of these figures, demand curves are portrayed for each of three customers, D_1, D_2, and D_3, respectively. Each demand curve traces out the quantity of electricity demanded (on the horizontal axis) for any corresponding price on the vertical axis.[6]

Figure A-6 depicts a standard inclining block rate where prices increase throughout the blocks (*e.g.*, the price for the first block is P_1 is less than that for the second block, P_2). Thus, the red stepped function depicts the supply curve for electricity facing these customers, and the demand curves cross the supply curves at points a, b, and c, respectively. Since customers 1 and 3 consume electricity in the middle of blocks 1 and 2 (points a and c, respectively), there would seem to be no serious modeling issues. By contrast, there is some ambiguity for customer 2, who consumes at the end point of block one. It is therefore necessary for the model to consider the customer's choice of block in addition to their point of consumption within that block.

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[6] There are many reasons why there are distinct demand curves for customers. Even if these customers had similar preferences (*e.g.*, utility functions), one explanation for the different positions of the curves could be that the incomes of these customers increases as one moves from demand curve D_1 to D_2 and then to D_3.

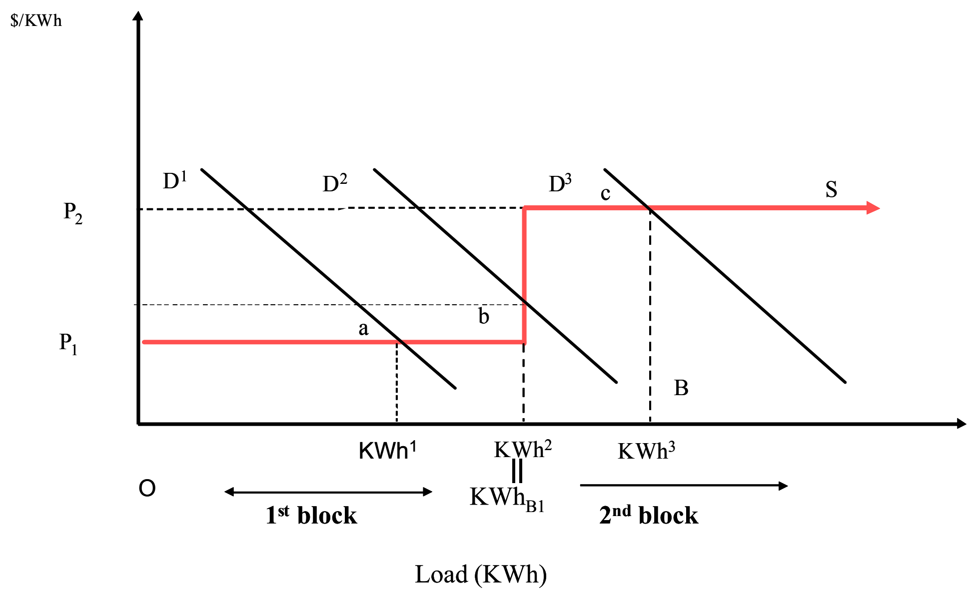

Figure A-6
Demand for Electricity under Inclining Block Rates (convex budget)

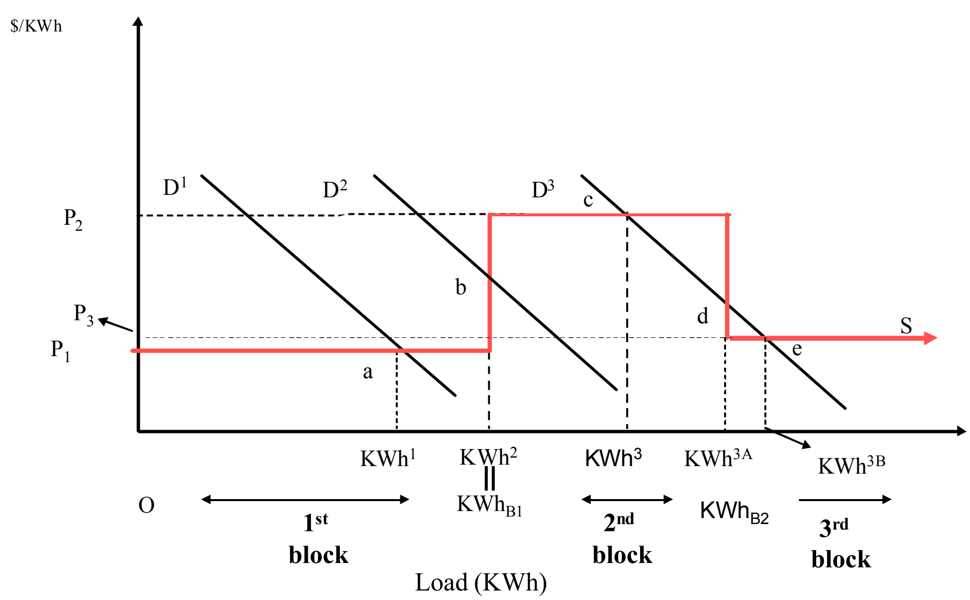

Figure A-7
Demand for Electricity under Inclining Block Rates (non-convex budget)

As is the case in Figure A-5, Figure A-7 illustrates the additional modeling difficulties associated with the fact that the CAP IBR has a final block whose price (illustrated in the figure by P_3) is below the price of the previous block, P_2. The additional modeling difficulty brought about this final declining block is evident by the fact that the demand curve for customer 3 (D_3) crosses the supply curve at three separate points (e.g. Strong and Smith 2010). Point c is in the middle of block 2; point e is in the middle of block 3; and point d is at the end point of block 2—or is it really at the beginning of block 3? The discrete choice as to the last block is again a critical part of the empirical model to estimate electricity demand response to this block rate, but again, they are not uniquely ranks choices. The formal modeling of this feature of the block rate design is problematic, and these issues will be addressed in the final report to be prepared later in the year once a full year's data have been obtained. We now return to a discussion of demand model estimation needed for the other four rate treatments in the CAP.

Estimation of the Indirect Utility Functions and the Daily Demand for Electricity

To estimate the separable indirect utility functions discussed above and derive important characteristics about the demand for electricity, one must first identify the stage of the decision process to be estimated, select a particular functional form to be estimated, and determine the number of time periods to include. Over the past 30 years, these issues have been addressed in a variety of ways, both theoretically and within the context of the analysis of data from previous pilot studies.

Because of the nature of several of the rate treatments in the CAP and ComEd's focus on the effects of these rates on customers' allocations of electricity usage between the peak (1:00 pm to 5:00 pm weekdays) and off-peak hours, a compelling strategy is to focus on stage 1 of the decision process and to model electricity usage for these two time periods.[7] This strategy is particularly appropriate for the CPP and PTR treatments where, in addition to the routine price variation throughout the day as in the TOU and the DA-RTP treatments, these rate treatments involve acute high prices during the peak hours. Thus, it is especially important to focus on the

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[7] Due to the continuous nature of electricity supply and usage, defining what constitutes peak and off-peak is generally treated as an empirical question driven by prices and the circumstances by which customers use and value electricity. Studies of price response to time-of-use (TOU) rates typically utilize either pooled data for customers participating in different TOU rates or data that are pooled across several treatments where prices or the definition of the peak period (and or shoulder period) vary by the experimental design (*e.g.*, Caves, *et al*. 1984a,b; Patrick 1990; Braithwait 2000). To study this issue in greater depth and to establish a uniform definition of peak and off-peak electric energy as distinct electricity commodities, Caves *et al*. (1987) identified six separate commodities facing customers. A six-hour peak-pricing period was divided into one two-hour commodity and one four-hour commodity. Other hours are aggregated into four separate commodities. The authors argued that this sub-aggregation was needed to characterize behavior in response to prices that are high for only very short periods.

To extend that structure to hourly RTP-type programs, one would need to define 24 electricity commodities. Such an extensive specification would be warranted only if customers did adjust usage on an ongoing basis to changing hourly prices. Recently, Taylor, *et al.* (2005) analyzed the hourly price elasticity of commercial and industrial customers served under a day-ahead RTP rate to identify patterns where electricity use in certain hours was a complement or a substitute for electricity use in other hours. They report that generally electricity use during several consecutive afternoon hours appears to be complementary, thus constituting a single electricity commodity. In turn, this single commodity exhibits a substitution relationship with electricity use during the other hours of the day. These results confirm an earlier conclusion of Patrick and Wolak (2001). When combined, these studies offer strong empirical support for our use of a peak/off-peak specification.

There is also compelling evidence from customers that they implicitly characterize the day as being comprised of peak and off-peak period (Neenan, *et al*. 2002a,b and 2003). While the specification of what comprises the peak hours may be customer specific, common business practices, driven in large part by traditional rate structures, support a bifurcation of the day that captures most of the variation in usage.

extent to which these episodic prices, as well as the routine variation in prices, affect electricity demand during these peak hours. This is the primary focus of the recently released empirical evaluation of the PowerCents DC™ program (eMeter Consulting 2010). For completeness and to facilitate comparison with the results from this other important pilot program, part of the focus of our analysis will be to examine the extent to which ComEd's TOU, DA-RTP, CPP, and PTR rate treatments reduce electricity usage during the peak hours.

For a complete evaluation, however, it is also critically important to understand if the episodic prices and the routine price variations in these hours embodied in the TOU and DA-RTP treatments cause customers to shift usage from peak hours to off-peak hours, or if the rate treatments just lead to an overall reduction in demand. Without such an extended analysis, it is impossible to determine if customers in CPP and PTR rate treatments substitute off-peak for peak electricity usage at the same rate as customers in the other treatment groups. It could be the case that customers in CPP and PTR rate treatments actually substitute off-peak for peak electricity usage at a greater rate than customers in other rate treatments.

Much of the literature regarding the choice of an empirical specification for modeling the effects of alternative rate structures on peak and off-peak electricity usage focuses on the need to retain the consistency with economic theory, but it also recognizes the realities of the data that are available. Models differ in their algebraic form, in the extent to which they are globally or only locally consistent with economic theory, and in the ease of econometric estimation.

At one end of the spectrum, a number of studies have relied on a constant elasticity of substitution (CES) specification (e.g., Caves, *et al*. 1984a,b; Herriges, *et al*. 1993; and Braithwait 2000), which assumes that the elasticity of substitution between peak and off-peak electricity usage is constant regardless of the peak to off-peak price ratio.[8] This approach has a distinct advantage in being able to model changes in overall electricity usage (stage two of our decision process) through a nested algebraic structure. An important focus of our study is to investigate the extent to which the elasticity of substitution depends on the ratios of electricity prices in the peak and off-peak periods rather than on the absolute levels of those prices.[9] Hence, we require a demand model that does not impose the CES restriction.

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[8] It is easy to estimate the elasticity of substitution (σ) from the CES model through the following relation. By letting K_p and K_o be peak and off-peak electricity use, respectively, and P_o and P_p be off-peak and peak prices, respectively, the elasticity of substitution can be estimated by ordinary least squares using the following equation: $\ln(K_p/K_o) = a + \sigma \ln(P_o/P_p)$. Since the CES function is what is known in the literature as a self-dual function, this empirical equation for the elasticity of substitution can be derived from either the direct utility function separable in peak and off-peak electricity or through the derivation of the indirect utility function and an application of Roy's identity. The self-dual property (where the direct function, and its indirect counterpart are of the same algebraic form) of the CES form is most commonly derived through the application of Shepard's lemma to a CES production function and its dual cost function derived from a problem to minimize the cost of producing a fixed output from inputs supplied at fixed prices (e.g. Silberberg and Suen 2001, pp. 238-248). Through the application of Roy's identity, a similar derivation applies to the problem of maximizing customer utility subject to a budget constraint (e.g. Silberberg and Suen 2001, p. 268).

[9] In an early study of pricing experiments, Caves and Christensen (1980c) found that elasticities of substitution varied substantially with price.

There are a number of second-order flexible form models that do not restrict *a priori* the elasticity of substitution to be constant. One such commonly used flexible form, the translog (TL) model, has been used most extensively in the production economics literature to measure the elasticities of substitution between productive inputs through the specification of an indirect cost or profit function (*e.g.*, Chambers 1988, Berndt 1991). It can also be applied in a customer demand context to specify an indirect utility function (*e.g.*, Cornes 1992; Deaton and Muellbauer 1980; Caves and Christensen 1980a). An attractive feature of this TL model in this context is that it relies on the estimation of a set of electricity expenditure share equations that are linear in the model parameters. The estimates of the elasticity of substitution are functions of the estimated model parameters and the estimated expenditure shares (Caves and Christensen 1980c). In this way, the elasticities of substitution can differ at each data point: rather than being constant, they are potentially a function of the peak to off-peak price ratio. Once the model is estimated, this hypothesis could be tested by regressing the estimated elasticities of substitution against the price ratios and other explanatory variables.

While this TL form is particularly attractive from an estimation perspective, Caves and Christensen (1980 a,b) argue that the TL model does not perform well when substitution elasticities are likely to be small, or when there are likely to be small expenditure shares or large relative differences among expenditure shares. This is partly true because the translog has as a special case the Cobb-Douglas form, which has a constant elasticity of substitution equal to one—implying that the ratio of peak to off-peak electricity usage always falls by 1% for each 1% rise in the peak to off-peak price ratio. Since it is unlikely that residential customers are able or willing to change electricity off-peak for peak consumption at such a high rate in response to changes in prices, this TL form, in contrast to its use in other empirical applications, has not been widely used in the study of electricity demand. In cases where its performance was compared to other empirical specifications, other forms nearly always performed better. This was true for Caves and Christensen (1980c); and much more recently, Patrick and Wolak (2001) also found the TL to be problematic in an application of customer demand for electricity under real-time pricing.

In both these cases, and in other applications as well (*e.g.*, Boisvert 2007, Taylor and Schwarz 1990), there is some agreement that another flexible form, the Generalized Leontief (GL) model, is superior to the TL model in representing electricity demand. Because the GL model has a fixed-coefficient Leontief technology as a limiting special case (*e.g.*, as depicted in Figure A-2 above), it has the advantage of more easily capturing the rather modest substitution possibilities that are likely to be found between residential peak and off-peak electricity use. On the other hand, the GL model has the drawback of losing some of its flexibility if one imposes global concavity — in such a case, all inputs must be substitutes.

To circumvent the difficulties related to both the TL and GL models, Patrick and Wolak (2001) and Taylor, *et al.* (2005) employ a Generalized McFadden (GM) function that is "…second-order flexible, yet suited to capture small positive and negative elasticities of substitution between electricity demands across load periods within a day" (Patrick and Wolak 2001, p. 27). The need to accommodate both positive and negative elasticities of substitution results from their specification of more than two demand periods. Because the CAP analysis requires specification of only two demand periods, the two electricity commodities must be substitutes, and the primary rationale for the selection of the GM model in these other studies is of no concern in our present application of the GL indirect utility function. We now proceed to a formal presentation of the GL model.

The Generalized Leontief Indirect Utility Function

For the n commodity case ($i = 1 \ldots n$), the generalized Leontief (GL) indirect utility function is given by:

$$(2) \qquad V = \frac{2}{\sum_i \delta_i \sqrt{P_i/Y} + \sum_i \sum_j \gamma_{ij} \sqrt{P_i/Y} \sqrt{P_j/Y}}$$

where V is indirect utility, P_i are commodity prices, and Y is total expenditures. The parameters of the function are δ_i and γ_{ij}, where $\gamma_{ij} = \gamma_{ji}$.

Caves and Christensen (1980a) show that for equation (2), the budget share equations can be written as:

$$(3) \qquad w_i = \frac{\left\{\delta_i \sqrt{P_i/Y} + \sum_j \gamma_{ij} \sqrt{P_i/Y} \sqrt{P_j/Y}\right\}}{\sum_i \delta_i \sqrt{P_i/Y} + \sum_i \sum_j \gamma_{ij} \sqrt{P_i/Y} \sqrt{P_j/Y}}$$

where w_i is the share of total expenditures spent on commodity i. For the GL indirect utility function to be separable in peak and off-peak electricity use, it must also be homothetic, which mathematically requires that $\delta_i = 0$ for all i.

The Two-Commodity Specification for Peak and Off-Peak Electricity Demand

If we define P_p and P_o as the prices of peak and off-peak electricity, respectively, and ES_p and ES_o as the shares of electricity expenditure in peak and off-peak periods, respectively, then the two-commodity homothetic GL indirect utility function and budget shares for electricity can be written as:

$$(4) \qquad V = \frac{Y}{\gamma_{pp} P_p + 2\gamma_{po} \sqrt{P_p P_o} + \gamma_{oo} P_o}$$

$$(5) \qquad ES_p = \frac{\gamma_{pp} P_p + \gamma_{po} \sqrt{P_p P_o}}{\gamma_{pp} P_p + 2\gamma_{po} \sqrt{P_p P_o} + \gamma_{oo} P_o}$$

(6) $$ES_o = \frac{\gamma_{oo} P_o + \gamma_{po}\sqrt{P_p P_o}}{\gamma_{pp} P_p + 2\gamma_{po}\sqrt{P_p P_o} + \gamma_{oo} P_o}$$

The budget share equations are homogeneous of degree zero in γ_{pp}, γ_{po}, and γ_{oo}.[10] Thus, without loss of generality, we can adopt the normalization of $\gamma_{pp} + 2\gamma_{po} + \gamma_{oo} = 1$.

For the two-commodity homothetic GL model, Caves and Christensen (1980a) show that the elasticity of substitution between peak and off-peak electricity can be written as:

(7) $$\sigma_{po} = \frac{\gamma_{po}\sqrt{P_p P_o}}{2ES_p\left(1 - ES_p\right)\left(\gamma_{pp} P_p + 2\gamma_{po}\sqrt{P_p P_o} + \gamma_{oo} P_o\right)}.$$

Through an examination of equation (7), it is clear that for any given set of parameters (either assumed or estimated from data), the elasticity of substitution is a function of both the estimated parameters of the function and the prices. Furthermore, σ, ES_p, and ES_o can all be nonnegative only if γ_{po} is nonnegative.[11] There is no restriction, however, on the signs of γ_{pp} and γ_{oo}.[12] In the extreme case where $\gamma_{po} = 0$, the elasticity of substitution is zero, consistent with the case described in Figure A-2 above. The null hypothesis that the elasticity of substitution between peak and off-peak electricity consumption is zero is thus conveniently tested using the GL demand model.

The Estimating Equations

To estimate the elasticities of substitution in equation (7), we must have estimates of the parameters of the indirect utility function in equation (4). It cannot be estimated directly because

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[10] "Homogeneity of degree zero" means that budget shares do not change if all prices and expenditures change in the same proportion.

[11] This is sufficient for the indirect utility to satisfy the monotonicity requirement; that is, $\partial V/\partial p_i < 0$ for all i.

[12] We must also test that the quasi-convexity requirement on V is met at each data point. This is equivalent to the requirement that the matrix of Allen partial elasticities of substitution be negative semi-definite (Berndt 1991). The cross Allen partial elasticities of substitution are symmetric: $\sigma_{po} = \sigma_{op}$. To do the test for quasi-convexity, however, we must also calculate the own Allen elasticities of substitution, σ_{pp} and σ_{oo}, so that we have the complete matrix of Allen elasticities.

For the two goods case, one can calculate these own Allen elasticities from the expenditure shares and the cross Allen partial elasticity of substitution. One can first recall from Berndt (1991) that when these own Allen elasticities are multiplied by expenditure shares, one has expressions for the compensated own-price elasticities of demand—the percentage change in the demand for peak or off-peak electricity due to percentage changes in their own prices that will leave a customer's utility unchanged; the elasticities are: $E_{pp} = w_p\, \sigma_{pp}$ and $E_{oo} = w_o\, \sigma_{oo}$, respectively. Furthermore, compensated cross price elasticities [the percentage change in peak (off-peak) demand due to a percentage change in the off-peak (peak) price] are similarly given by: $E_{po} = ES_o\, \sigma_{po}$ and $E_{op} = ES_p \sigma_{op}$, respectively. Since these compensated price elasticities must satisfy adding up conditions to ensure homogeneity of demand, we also know that: $ES_p\, \sigma_{pp} + ES_o\, \sigma_{po} = 0$, and $ES_p \sigma_{op} + ES_o\, \sigma_{oo} = 0$. Thus, we can solve for: $\sigma_{pp} = -(ES_o/ES_p)\, \sigma_{po}$ and $\sigma_{oo} = -(ES_p/ES_o)\, \sigma_{po}$. By calculating the own Allen elasticities in this way, one can also ensure the internal consistency of the empirical results.

we have no data for customers' utility levels V. Because we can derive the electricity expenditure share equations from equation (4), we can obtain estimates of the parameters of V by estimating the share equations (5) and (6). However, a strategy for doing this is not completely straightforward. To estimate the share equations directly would require a non-linear systems estimator that applies cross-equation constraints on every parameter. It is necessary to impose the normalization on the parameters by adding an additional constraint where $\gamma_{pp} + 2\gamma_{po} + \gamma_{oo} = 1$.

As an alternative, we can simplify the estimation by first forming an equation for the ratio of expenditure shares. Because the denominators of these share equations are identical, we are left with a single equation that is simpler than either equation (5) or (6):

$$(8) \qquad \frac{ES_p}{ES_o} = \frac{\gamma_{pp} P_p + \gamma_{po} \sqrt{P_p P_o}}{\gamma_{oo} P_o + \gamma_{po} \sqrt{P_p P_o}}$$

This is still an equation that is non-linear in the parameters, but the estimation is reduced to that of a single equation in which only symmetry need be imposed on the coefficient γ_{po}. It is still necessary to impose the normalization on the parameters by adding an additional constraint where $\gamma_{pp} + 2\gamma_{po} + \gamma_{oo} = 1$. Furthermore, past experience (*e.g.*, Boisvert, *et al*. 2007), Braithwait 2000, Caves and Christensen 1984 a,b) suggests that the estimation is facilitated by transforming the equation into logarithms, as follows:

$$(9) \qquad \ln\left(ES_p / ES_o\right) = \ln\left[\gamma_{pp} P_p + \gamma_{po} \sqrt{P_p P_o}\right] - \ln\left[\gamma_{oo} P_o + \gamma_{po} \sqrt{P_p P_o}\right] + u$$

where u is a stochastic error term.

An Empirical Specification for ComEd's Electricity Rate Treatments

Because the rates differ by time of day in ComEd's TOU, DA-RTP, CPP, and PTR rate treatments, the model in equation (9) can be used to estimate the parameters necessary to calculate the elasticities of substitution for customers in these four treatment groups. To conduct the estimation, we must first use the customers' hourly data on electricity prices and usage to create observations on peak and off-peak expenditure shares and average prices (perhaps weighted by hourly usage). This will create one observation per customer per day. By letting the observations for the t^{th} day be denoted by the subscript t, we have for each customer in each treatment group the following equation:

$$(10) \qquad \ln\left(ES_{pt} / ES_{ot}\right) = \ln\left[\gamma_{pp} P_{pt} + \gamma_{po} \sqrt{P_{pt} P_{ot}}\right] - \ln\left[\gamma_{oo} P_{ot} + \gamma_{po} \sqrt{P_{pt} P_{ot}}\right] + u_t$$

To normalize the coefficients, this equation would be estimated subject to the following constraints, the latter of which is required by Young's Theorem:

(10a) $\gamma_{pp} + 2\gamma_{po} + \gamma_{oo} = 1$, and $\gamma_{op} = \gamma_{po}$

Because of the large numbers of customers in each treatment and of daily observations per customer, we estimate the model for each customer in each treatment. In this way, the firm level effects are reflected in the daily estimates of the elasticities of substitution. Tests of the differences in the elasticities of substitution by treatment or by customer characteristic will be conducted in a second regression analysis. In this analysis, the daily estimates of the elasticities of substitution by customer will be pooled across customers and treatments. These pooled estimates will be regressed against peak to off-peak price ratios, variables controlling for individual customer characteristics, and dummy variables to control for the rate treatment effects. This strategy is similar to that employed by Boisvert, *et al*. (2007) and Taylor and Schwarz (1990). The exact specification of this regression will depend on the nature of customer-specific data that are available through the survey responses or other sources of data. Thus, this second regression analysis will not be performed as part of this preliminary analysis. It will be conducted as part of the final analysis when the entire year's price data are available and the survey responses have been completed.

It is possible and appropriate to reflect differences in daily weather conditions in the regressions for individual customers. For example, Boisvert, *et al*. (2007) control for the effects of weather by including two additional variables. The first variable, CD_t, measures cooling degrees, and it enters as an intercept shifter, thus controlling for differences in peak to off-peak usage as temperature changes. Variable H_t takes on the binary values of unity for hot days and zero otherwise, where a hot day is defined as one in which a heat index is above 85^{o}. Assuming two weather-related variables such as these are included, the estimating equations become:

(11) $\ln\left(ES_{pt}/ES_{ot}\right) = cd(CD_t) + \ln\left[h_p H_t + \gamma_{pp}P_{pt} + \gamma_{po}\sqrt{P_{pt}P_{ot}}\right] - \ln\left[h_o H_t + \gamma_{oo}P_{ot} + \gamma_{po}\sqrt{P_{pt}P_{ot}} + \right] + u_t$.

We also need:

(11a) $\gamma_{pp} + 2\gamma_{po} + \gamma_{oo} = 1$;

(11b) $h_p = h_o$; and

(11b) $\gamma_{op} = \gamma_{po}$.

Estimating the Daily Elasticities of Substitution

Once equation (11) is estimated, the parameter estimates are used to calculate the daily elasticities of substitution between peak and off-peak electricity use. As is evident from equation (7), we must first calculate predicted values for the peak and off-peak expenditure shares. In the standard formulation of the GL model, one could simply substitute the estimated parameters into equations (5) and (6). However, once the weather variables have been introduced into the model, one must calculate the predicted value for ES_{pt} directly from equation (11) in the following way.

We can first substitute the estimated parameters (denoted by a "^") directly into equation (11):

(12) $\ln(\hat{ES}_{pt} / \hat{ES}_{ot}) = \hat{cd}\; CD_t + \ln[\hat{h}_p\; H_t + \hat{\gamma}_{pp}\; P_{pt} + \hat{\gamma}_{po}\sqrt{P_{pt}P_{ot}}\,] - \ln[\hat{h}_o\; H_t + \hat{\gamma}_{oo}\; P_{ot} + \hat{\gamma}_{po}\sqrt{P_{pt}P_{ot}}\,]$

Taking the anti-log of equation (12), we have:

$$(13) \qquad \hat{ES}_{pt} / \hat{ES}_{ot} = [e^{\hat{cd}\, CD_t}] \frac{[\hat{h}_p\, H_t + \hat{\gamma}_{pp}\, P_{pt} + \hat{\gamma}_{po} \sqrt{P_{pt} P_{ot}}\,]}{[\hat{h}_o\, H_t + \hat{\gamma}_{oo}\, P_{ot} + \hat{\gamma}_{po} \sqrt{P_{pt} P_{ot}}\,]} .$$

Since the two expenditure shares sum to unity,

$$(14) \ \hat{ES}_{pt} + \hat{ES}_{ot} = 1 ,$$

we can solve equation (14) for the off-peak expenditure share, and substitute the result into equation (13). After some rearranging, we have:

$$(15) \ \hat{ES}_{pt} = [e^{\hat{cd}\, CD_t}] \frac{[\hat{h}_p\, H_t + \hat{\gamma}_{pp}\, P_{pt} + \hat{\gamma}_{po} \sqrt{P_{pt} P_{ot}}\,]}{[\hat{h}_o\, H_t + \hat{\gamma}_{oo}\, P_{ot} + \hat{\gamma}_{po} \sqrt{P_{pt} P_{ot}}\,]} (1 - \hat{ES}_{pt}) .$$

Solving this equation for the predicted peak expenditure share, we have:

$$(16) \ \hat{ES}_{pt} = \frac{[e^{\hat{cd}\, CD_t}] \dfrac{[\hat{h}_p\, H_t + \hat{\gamma}_{pp}\, P_{pt} + \hat{\gamma}_{po} \sqrt{P_{pt} P_{ot}}\,]}{[\hat{h}_o\, H_t + \hat{\gamma}_{oo}\, P_{ot} + \hat{\gamma}_{po} \sqrt{P_{pt} P_{ot}}\,]}}{[1 + e^{\hat{cd}\, CD_t}] \dfrac{[\hat{h}_p\, H_t + \hat{\gamma}_{pp}\, P_{pt} + \hat{\gamma}_{po} \sqrt{P_{pt} P_{ot}}\,]}{[\hat{h}_o\, H_t + \hat{\gamma}_{oo}\, P_{ot} + \hat{\gamma}_{po} \sqrt{P_{pt} P_{ot}}\,]}} .$$

In the standard GL model (without the weather variables), we know that the underlying utility function is globally quasi-convex if all the γ parameters are strictly positive. In this case, we are guaranteed that this peak expenditure share is between zero and unity. By including the weather variables, it is clear that the peak expenditure share, and therefore the off-peak expenditure share, will differ by hot and cool days and by the number of cooling degrees depending on their values for these days. Furthermore, we are guaranteed that this peak expenditure share is between zero and unity if the terms $h_p\, H_t$ and $h_o\, H_t$ and parameters are positive as well. If these two terms are negative, then their absolute values must be smaller than the corresponding positive expressions in (16) in each of the numerators and denominators of equation (16) to guarantee that the shares are positive and add to unity. Because of the complexity added to the model by the inclusion of these weather variables, we must evaluate the principal minors of the matrix of Allen elasticities to determine if the underlying utility function is quasi-convex at every data point. In all cases, it is necessary for $\gamma_{po} > 0$, but this need not necessarily be the case for γ_{pp} or γ_{oo}.

Finally, these estimated relationships can be substituted into the expressions for the daily Allen elasticity of substitution between peak and off-peak electricity consumption:

(17) $$\hat{\sigma}_{pot} = \frac{\hat{\gamma}_{po}\sqrt{P_{pt}P_{ot}}}{2\,\hat{ES}_{pt}(1-\hat{ES}_{pt})(\hat{\gamma}_{pp}\,P_{pt} + 2\,\hat{\gamma}_{po}\sqrt{P_{pt}P_{ot}} + \hat{\gamma}_{oo}\,P_{ot})}.$$

From equation (16) above, it is evident that the two weather variables affect the size of the peak expenditure share. In turn, the size of the elasticity of substitution is also a function of this share because of the term: $\frac{1}{\hat{ES}_{pt}(1-\hat{ES}_{pt})}$. This term decreases [as does $(\hat{\sigma}_{po})$] as $\hat{ES}_{pt}$ increases for $0 < \hat{ES}_{pt} < 0.5$. The term reaches a minimum at $\hat{ES}_{pt} = 0.5$ and then increases [as does $(\hat{\sigma}_{po})$] for $0.5 < \hat{ES}_{pt} < 1.0$.

It follows immediately that one can also calculate internally consistent estimates of their own Allen elasticities of substitution that are needed to check the quasi-convexity requirement on *V* at each data point:

(18) $$\hat{\sigma}_{ppt} = \frac{\hat{ES}_{ot}}{\hat{ES}_{pt}}\hat{\sigma}_{pot}$$

(19) $$\hat{\sigma}_{oot} = \frac{\hat{ES}_{pt}}{\hat{ES}_{ot}}\hat{\sigma}_{pot}\ .$$

To check the quasi-convexity requirement on *V* at each data point, we need to check that (Berndt 1991):

$$\hat{\sigma}_{ppt} \le 0;\quad \text{and}\quad \hat{\sigma}_{oot} \le 0;\quad \text{and}\quad (\hat{\sigma}_{ppt})(\hat{\sigma}_{oot}) - (\hat{\sigma}_{pot})^2 \ge 0.$$

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B
OTHER ANALYTIC METHODS

In addition to the customer demand modeling described in the preceding appendix, four other types of analysis methods have been or will be used to meet the needs of various elements of the CAP evaluation. These are summarized in this appendix.

Analysis of Variance

Many of the hypotheses are addressed using some form of analysis of variance (ANOVA) or analysis of covariance (ANCOVA). These are formal statistical protocols for comparing differences between the mean values of outcomes (e.g., differences in overall energy consumption or peak-period usage) for two or more customer groups (applications). For example, ANOVA may be used to assess the difference in summer peak-period usage between a treatment and control group during the pilot period. In practice, these methods are implemented by means of equivalent regression methods using indicator (e.g., "dummy") variables for relevant treatment groups.[13] Such implementation provides rigorous statistical results from which the statistical significance of load differences among applications may be determined.

The analyses have been conducted using ordinary least squares (OLS) regressions with indicator variables for each treatment. This is equivalent to ANOVA and facilitates simultaneous comparisons across many treatments. The primarily OLS regression model is as follows:

$$\begin{aligned} Usage_i \;=\; & \alpha + \beta_{\mathrm{CPP}} \text{ x } \mathrm{CPP}_i + \beta_{\mathrm{RTP}} \text{ x } \mathrm{RTP}_i + \beta_{\mathrm{PTR}} \text{ x } \mathrm{PTR}_i + \beta_{\mathrm{TOU}} \text{ x } \mathrm{TOU}_i + \beta_{\mathrm{BIHD}} \text{ x } \mathrm{BIHD}_i \\ & + \beta_{\mathrm{AIHD}} \text{ x } \mathrm{AIHD}_i + \beta_{\mathrm{PCT}} \text{ x } \mathrm{PCT}_i + \beta_{\mathrm{Bill\_prot}} \text{ x } \mathrm{Bill\_prot}_i + \beta_{\mathrm{Purch}} \text{ x } \mathrm{Purch}_i \\ & + \beta_{\mathrm{Educ}} \text{ x } \mathrm{Educ}_i + \beta_{\mathrm{SFSH}} \text{ x } \mathrm{SFSH}_i + \beta_{\mathrm{MFNS}} \text{ x } \mathrm{MFNS}_i + \beta_{\mathrm{MFSH}} \text{ x } \mathrm{MFSH}_i + \mathrm{e}_i \end{aligned}$$

where *i* indexes customers, *a* is the constant term (the effect associated with the specified control group), the βs are estimated parameters (the revealed treatment effects), and e_i is the error term.

Several data issues have complicated the implementation of ANOVA-style models. For example, the relevant time periods are not the same for all customers. Customer CAP hourly load data begin on different dates; customers will end participation in the program on different dates (because they opted out or they ended service); enabling devices were installed and/or activated on different dates; and at least two service outages occurred for several hundred participating customers. An ANOVA-style comparison of average usage between two cells requires that such complicating factors (outside of the pilot administrator's control) be randomly distributed across the applications and hence do not affect the comparisons of means. Our analysis plan assumes

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[13] P. Kennedy, *A Guide to Econometrics*, Third Edition, 1992, pp. 226-227.

such a random distribution. In addition, EPRI has placed some restrictions on the data used in the hypothesis tests, such as including only customers with data for all days in June through August; and for whom no more than 2% of the observations are equal to zero.[14]

Load Impact Estimation

For episodic programs such as CPP and PTR, event-day load impacts are among the most relevant measures of program performance. EPRI estimated cell-level regression models (aggregating the customer-level data into single load profile) for each of the CPP and PTR applications. These models have hourly kWh as the dependent variable, and have explanatory variables that account for typical hourly usage patterns and the effect of weather on usage. The explanatory variables of primary interest are the hourly indicator variables for each hour of every event day. The coefficients on these variables are estimates of the change in usage during that event hour relative to a counterfactual reference load representing what the customer would have used in the absence of the event.[15]

EPRI has also estimated cell-level models with daily average peak-period usage as the dependent variable. These simpler models (relative to the hourly models) are another means of identifying demand response on event days, where non-event day usage (adjusted for weather conditions) is the basis of comparison. Finally, similar to the demand modeling, EPRI has estimated customer-level load impact equations for each customer in the CPP, PTR, and DA-RTP cells in order to examine the distribution of load impacts across customers of different types.

Choice Modeling

Formal choice models are used to test some hypotheses. These are regression-based models in which the left-hand-side variable indicates a customer decision (e.g., to adopt a technology) and the right-hand-side (or explanatory) variables are customer characteristics (e.g., electric space heating vs. non-electric space heating) and descriptions of the treatments (i.e., rate type) to which the customer has been exposed. These models seek to explain the effect of various factors on customers' decisions. In this way, they are functionally similar to commonly used Ordinary Least Squares (OLS) regression models. Choice models (e.g., logit) are distinguished from OLS models by explicitly accounting for the fact that they model an outcome that is expressed as a one or zero (e.g., yes/no, buy/not buy). OLS models applied to such an outcome can produce predicted values that are outside of the one/zero range.

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[14] An alternative is to employ a more complex regression model. For example, we could use monthly customer data, so the dependent variable would be the average usage for each customer in each month. The independent variables would control for the share of the month in which the customer was enrolled, had equipment installed, or experienced a service outage. Such a model may also benefit from the introduction of customer fixed effects that control for customer-specific characteristics that do not change during the sample timeframe. This modeling structure is capable of accounting for the data issues described above, but at the cost of complicating the analysis.

[15] The reference load is equal to the estimated load impact plus the observed (metered load). The regression model removes the need to calculate baseline loads that are used for PTR settlement purposes. However, it will be useful to compare the regression-based load impacts to the load impacts derived from the PTR baselines.

C
DATA ISSUES

The data to support the analysis come from several sources. Together, they comprise the database data used in the project assessment and evaluation. These data include the following:

- Hourly interval load data for each sample customer in all treatment and control group cells
- Monthly billing data (kWh, per unit energy prices, total cost, rebates paid) for each sample customer
- Initial and exit survey data for those participants who respond (to be collected)[16]
- Hourly prices faced by the CPP, PTR and DA-RTP customers
- Event day information
- Device performance information, including AMI meters, in-home devices, and other technologies
- Customer interaction data on all touch-point contacts from ComEd to the sample participants; and by the participants to the program website or ComEd customer support center.

This Phase 1 report uses data for June through August 2010, while the Phase 2 report will use data for the entire study year ending May 2011.

Survey data are required to test some of the hypotheses and to conduct some sensitivity analyses, such as whether effects differ by income level. Some of the survey data (e.g., customer satisfaction) will not be obtained until the end of the pilot period, at which time customers will be asked to fill out a survey that asks (among other things) about their experiences on the pilot. Other data (e.g., income categories) are also available in the customer surveys given to CAP participants. However, relatively low survey response rates (below about 75%) would limit the ability to make comparisons across these groups. The EPRI project team will propose a survey content and administration plan that addresses the data needs and proposed means of its collection in sufficient volume and quality. Because the needed survey information is not yet available, this initial report does not include tests of hypotheses that require survey data.

The scope and validity of the results have been partially compromised by certain data limitations. These limitations are as follows:

1. There are serious problems with the composition of the control groups, F1 and F2, because these groups were created by selecting at random from load research samples that were incompletely stratified by customer size. As a result, high-usage customers are over-represented in each of the delivery class segments (e.g., single/multi-family and electric/non-electric space heat) of the F1 and F2 groups relative to what would be expected in the

[16] A high response rate is critical to achieving insightful and extensible results.

population. As a result, we are unable to test hypothesis H1, which is a comparison of cell F2 to F5 to test the effect of the meter on usage behavior. In addition, the test of hypothesis H6a, which is a comparison of cells F1 and F2 to test the effect of customer education, requires an assumption that the samples in the two cells are comparable to one another (even though they are not comparable to the other cells).

2. The IBR cells under-represent low-usage customers; so average hourly kW usage is 10%-15% higher for IBR than it is for other rate types and for the F3 control group. This occurs because selection to the IBR cells is restricted to customers with at least five years of billing history. Because smaller customers in multi-family units tend to move more frequently and therefore do not have five years of data, there are relatively fewer low-usage customers in the IBR treatment cells than in other cells. This precludes the full testing of hypothesis H2b (which can nonetheless be tested for the other rate structures), and indirectly affects the testing of many other hypotheses (including H2c, H2d, H2e, H3d, H3e, H4d, H5b, H6b, H6c, H7m, H7q, and H7u) because IBR customers must be excluded from these analyses. As a partial remedy, EPRI separately analyzed energy usage changes for IBR customers using the available monthly billing-level usage data for 2009 and 2010.

3. The in-home display technology (IHD) cells under-represent low-usage customers because they exclude customers in multi-family residences that are above the first floor of a residential building. This exclusion occurs because of technical limitations on IHDs' ability to function properly for customers residing above the first floor. The IHD treatment cells therefore include fewer multi-family residences than would be obtained in a random selection. Because multi-family residences tend to have relatively low average hourly kW usage, the IHD treatment cells have average hourly kW usage that is about 3% higher (and even higher for AIHD customers) than it is for eWeb customers without IHD. This issue affects the testing of hypotheses H3d, H3e, and H6b.

4. Customer acceptance of programmable controllable thermostat (PCTs) is low, less than 20% fulfilled. This precludes comprehensive testing the effects of the PCT enabling technology on customers' response to time-based rates such as CPP and PTR. As a result, the analysis of energy usage effects for the D4 and D8 groups employs an *intention-to-treat* design.[17] If sufficient numbers of PCTs are eventually installed, then attempts will be made to measure their impacts.

5. Very few customers purchased IHDs. Consequently, the customers in groups L5b and L6b may be analyzed under an assumption of intention to treat.

To the extent possible, EPRI has developed methods and hypothesis tests that mitigate the effects of these data issues.

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[17] Intention to treat is used in cases wherein a treatment was offered to a particular set of customers who largely (or entirely) declined to accept the treatment. Because they were offered a treatment, customers in such a treatment group cannot be considered as completely untreated, nor can they be treated like another untreated group. The intention-to-treat design in effect equates the response of customers that took the treatment but did not use it with those that did not take the treatment: in both cases the treatment effect is nil.

D
DETAILS OF THE CAP HYPOTHESIS TESTS

As part of the evaluation of the CAP pilot a number of hypotheses, numbered from H1 through H7v, are to be tested. These hypotheses can be grouped conveniently into several topic areas, and also for convenience this appendix is organized into several corresponding sub-sections. Within the sub-sections, each hypothesis is stated, along with a discussion of the analytical method needed to conduct the hypothesis test. Many of the hypotheses have been tested, and the results are reported in the Phase 1 report and this appendices document. By necessity, these tests are based on data from June through August, 2010.

Tests of some of the hypotheses require additional data that will not be available until the end of the pilot. Despite the need for additional data, the structures of these hypothesis tests are still specified in this appendix, with full recognition that these tests will be performed as part of the Phase 2 analysis. The results of these tests will be provided in the final report. It is also likely that the tests of the other hypotheses, the results of which appear below, will be updated based on additional data forthcoming during the rest of the pilot. This could be particularly important because the test results below do not include data from the one event day called during the month of September, 2010.

Throughout the discussion in this appendix, we make numerous references to specific treatment (also referred to as application) cells that contain the groups of customers whose behavior relates to the hypotheses being tested. These cells are referenced by the alpha-numeric ID's found in Figure 3-1 in EPRI 1022703. These IDs are descriptive of the experimental design in terms of rate and enabling technology treatments. In the tables in this appendix, many of these treatments are further identified with variable names, and these are defined in Chapter 7 of EPRI 1022703)

Meter Type

H1: Meter type has no effect on electricity usage behaviors.

This hypothesis is designed to isolate the effect of the installation of an AMI meter. To conduct the test, it would have been necessary to compare usage between customers in cell F2 (who have standard meters) and customers in group F5 (who have AMI meters). Unfortunately, as explained in Chapter 4 of EPRI 1022703), customers in groups F2 and F5 are not drawn from the same geographic region, and during an initial examination of the data, it became apparent that the two groups represent very different populations. Thus, we are unable to test this hypothesis.

Rate Treatments

The hypothesis tests related to the rate treatments are based upon comparisons of means of the data across the various treatment and control groups. The models are designed to test differences in the several measures of usage (e.g., average hourly usage) as a function of indicator variables that encompass the full range of treatment and control characteristics, including:

- Each rate treatment;
- Each technology treatment;
- Whether or not the customer was notified of bill protection;
- Whether the customer was offered the opportunity to purchase technology or was given the technology for free;
- Whether the customer received only basic AMI education or received the full education; and
- The type of housing unit each customer resides in, categorized in combinations of single or multi-family (SF or MF) and space heat or non-space heat (SH or NS).

These models facilitate comparisons between treatment and control groups and also between different treatment groups.

H2a: The IBR rate is most easily adopted by customers.

Ease of adoption is measured by the rates at which customers do not opt out of the CAP program anytime over the test year. A logistic regression model, in which the dependent variable takes on a value of unity if the customer opted out, and zero otherwise, is used to predict differences in opt-out rates for each of the rate treatments.

Table D-1 contains the results of this estimated model, in which the independent variables are indicator (dummy) variables for the rate treatments, technology, bill protection, education, housing type, and purchase characteristics. The estimated coefficients from these types of models can be used to simulate the probability that a customer with a particular set of treatments will opt out of the pilot.[18] The constant coefficient indicates that customers on the IBR rate, with no technology, in a single-family home with non-space heating, and who were not notified of bill protection, have a 0.34% probability of opting out of the pilot.[19] For the other rate treatments, the probability of opting out is derived from the sum of the constant coefficient plus the coefficient for the dummy variable associated with that rate and/or other treatment. For example, the probability of opting out increases to 3.08% for a customer on the CPP rate.[20] Note that the z-statistic of 3.74 on the CPP coefficient indicates that the difference in the probability of opting out for CPP customers compared with IBR customers is statistically significant.[21]

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[18] For details, see: EPRI 1022703, Section 2.

[19] For this customer type, based upon the -5.675 coefficient, the equation for calculating the probability of opt-out is exp(-5.675)/[1+exp(-5.675)].

[20] 3.08% equals exp(-5.675+2.226)/[1+exp(-5.675+2.226)].

[21] For z-statistics greater than 2.0 in absolute value, a coefficient to be statistically different from zero at least the 5% level of significance.

Based on these results, the statistically significant positive coefficients for the three dynamic rate treatments support the hypothesis that IBR customers opt out at rates that are significantly lower than do customers on all other rates except for those on the flat rate. Since the absolute value of the z-statistic for the coefficient on the dummy variable associated with flat rate is well below the critical value of 2.0, the probability of customers in the flat rate treatment not opting out of the pilot is not significantly different from the probability that customers in the IBR treatment opt out.[22]

Table D-1
Impacts of Rate Type on Opt Outs[23]

Variable	Coef.	S.E	z	Prob
Constant	**-5.675**	0.609	-9.32	0.34%
CPP	**2.226**	0.595	3.74	3.08%
DA-RTP	**1.399**	0.627	2.23	1.37%
FLR	-0.629	0.919	-0.68	0.18%
PTR	**1.830**	0.611	3.00	2.09%
TOU	**1.641**	0.622	2.64	1.74%
BIHD	**0.599**	0.245	2.45	0.62%
AIHD	0.141	0.279	0.51	0.39%
PCT	0.236	0.310	0.76	0.43%
Bill Protection	0.344	0.378	0.91	0.48%
Purchase	0.155	0.384	0.40	0.40%
Full Education	(omitted)			
SFSH	0.422	1.035	0.41	0.52%
MFNS	**-0.432**	0.188	-2.29	0.22%
MFSH	0.511	0.432	1.18	0.57%
Dependent variable: binary choice variable that equals one if the customer opted out of the pilot program and zero otherwise				

H2b: The IBR rate causes the greatest reduction in overall electricity usage during the year.

Because customers selected for the IBR treatment had to have at least five years of billing history, customers with lower usage are seriously under-represented in the IBR treatment.[24] For this reason, it is not possible to make meaningful comparisons of the impacts on usage between customers on the IBR rate with those on the other rates. However, it is still important to understand differences in the impacts of the other rate treatments on electricity usage. Therefore,

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[22] Very similar results were found for an alternate specification that included only the rate dummies.

[23] The regression is based upon 7,083 observations, and has a pseudo-R-squared value of 0.05. See Appendix E for additional details.

[24] For details see: EPRI 1022703, Chapter 4.

the test is redesigned to compare the impacts on usage among all the other rate treatments, and the tests are performed using ANOVA-style comparisons[25] in which the dependent variable is one of the four measures of usage discussed above in the text. That is, in the separate hypothesis tests described below, the comparisons of the effects on usage are based on three separate measures of usage. Thus, in many of the hypothesis tests below, the dependent variable for each customer in each of the regression equations is one of the following measures of usage:

1. Average kWh usage during all hours;
2. Average kWh usage during peak hours (1 to 5 p.m. on non-holiday weekdays, and alternatively on just event days); and
3. The average ratio of peak to off-peak usage.

To specify the models, each of these measures of usage is calculated across the entire available sample timeframe.[26] The independent variables in the regression equations account for the rate treatments and the treatments reflecting availability of different enabling technologies.

Table D-2 displays the results for the test of this modified hypothesis H2b. In this table, the constant term indicates overall usage (in units of average kWh per hour) for customers associated with the omitted categories (i.e., those customers on the flat rate, with no enabling technology, with no information about bill protection, with no technology offered for purchase, with SFNS housing, and with "basic" education). To calculate average usage for customers in other treatments, one need only sum the constant term and the coefficient for the dummy variable for that other treatment.

Put somewhat differently, each coefficient represents the difference in overall average usage (relative to the omitted category) due to the treatment. For example, because of the positive coefficient, customers on the CPP rate use 0.011 kWh per hour more electricity than do flat rate customers. Similarly, because of the positive coefficient, customers on the PTR rate use 0.011 kWh per hour more electricity than do flat rate customers. The absolute value of neither t-statistic is above 2.0; therefore neither coefficient is statistically significant. The negative and statistically significant coefficients on the multi-family housing unit variables (MFNS and MFSH) suggest that customers in multi-family residences use less electricity than customers in single-family residences with non-space heating.

As suggested in the text above, these results reinforce the key finding from other analyses of the aggregate data. That is, when taken together as groups, there appears to be no significant differences in overall electricity usage among customers on the alternative rates.

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[25] As used throughout this document, ANOVA generally includes analyses of variance and covariance, and may be undertaken using standard protocols or through an equivalent regression-based approach. See the discussion in Chapter 2 for details.

[26] Total usage is functionally equivalent to average usage if the sample is balanced.

Table D-2
Impacts of Rate Type on Electricity Usage[27]

Variable	Coef.	S.E.	t
Constant	**1.503**	0.053	28.21
CPP	0.011	0.040	0.26
DA-RTP	0.050	0.043	1.16
PTR	0.011	0.043	0.25
TOU	0.053	0.043	1.23
BIHD	-0.017	0.027	-0.61
AIHD	0.033	0.032	1.03
PCT	0.013	0.039	0.34
Bill Protection	0.028	0.048	0.58
Purchase Tech.	-0.057	0.048	-1.18
Full Education	-0.061	0.065	-0.94
SFSH	0.064	0.195	0.33
MFNS	**-0.744**	0.019	-39.87
MFSH	**-0.697**	0.080	-8.74
Dependent variable: average hourly kW usage for all days from June through August 2010.			

H2c: The CPP rate causes the greatest reduction in peak load during the summer.

This hypothesis is tested using a similar ANOVA-style comparison in which the dependent variable is each customer's average kWh usage during the peak period (1:00 p.m. to 5:00 p.m.) on summer, non-holiday weekdays. As in the regressions above, the independent variables account for the several rate and technology treatments. Two alternative tests of this hypothesis are developed, one in which average kWh usage is calculated for all summer peak hours; and a second in which average kWh usage is calculated for peak hours, but only for CPP/PTR event days. The hypothesis in the second case is that: a) the coefficient for CPP is negative; and b) the coefficient for CPP is more negative than those of the other rates.

Table D-3 contains the results of this test. Again the IBR customers are excluded from the analysis. In this table, the coefficients in columns 2 and 5 represent the differences in average peak-period (on all days and on event days, respectively) usage for the treatments versus customers in the excluded categories. For example, the coefficient on CPP of 0.044 indicates that

[27] The regression is based upon 5,262 observations, and has an R-squared value of 0.19.

CPP customers use an average of 0.044 kWh per hour more than flat rate customers (all else equal) during peak hours, although this difference is not statistically significant. The low t-statistics for the coefficients on the dummy variables for the rates indicate that there is no significant difference in consumption by rate treatment either for peak hours on all weekdays or for the peak hours on event days. A partial exception to this result is that the day-ahead RTP group (identified as "DA-RTP" in the table) has higher peak consumption (on all days) than does the flat rate group.

Table D-3
Impacts of Rate Type on Summer Peak Load[28]

	Peak Hours			Event Days		
Variable	**Coef.**	**Std. Err.**	**t**	**Coef.**	**Std. Err.**	**t**
Constant	**1.728**	0.067	25.77	**2.391**	0.099	24.20
CPP	0.044	0.046	0.94	-0.025	0.062	-0.41
DA-RTP	**0.115**	0.052	2.20	0.104	0.070	1.49
PTR	0.046	0.051	0.91	0.015	0.069	0.22
TOU	0.065	0.051	1.26	0.051	0.069	0.74
BIHD	-0.015	0.035	-0.43	-0.008	0.046	-0.18
AIHD	0.043	0.039	1.11	0.073	0.052	1.41
PCT	-0.017	0.047	-0.36	-0.019	0.063	-0.30
Bill Protection	0.049	0.063	0.79	0.074	0.083	0.88
Purchase Tech.	-0.054	0.062	-0.87	-0.082	0.080	-1.02
Full Education	-0.098	0.080	-1.23	-0.209	0.114	-1.83
SFSH	0.142	0.256	0.55	-0.066	0.311	-0.21
MFNS	**-0.969**	0.023	-41.65	**-1.317**	0.031	-42.37
MFSH	**-0.935**	0.055	-17.12	**-1.293**	0.072	-18.00
Dependent variables: "Peak Hours" refers to average hourly kW usage during peak hours on non-holiday weekdays from June through August 2010. "Event Days" refers to average hourly kW usage during peak hours on event days.						

H2d: The CPP rate causes flatter load shapes at all times during the year.

This hypothesis is tested using an ANOVA-style comparison in which the dependent variable is customers' average ratio of peak to off-peak usage, where the peak period is defined to include the hours 1 p.m. to 5 p.m. on non-holiday weekdays and the off-peak period includes all other hours. These ratios of peak to off-peak usage are calculated over the entire sample timeframe.

[28] Both regressions are based upon 5,262 observations, and have R-squared values of 0.21.

The independent variables account for the rate and technology treatments. The hypothesis is that: a) the coefficient for the CPP variable is negative; and b) the coefficient for the CPP variable is more negative than those of the other rates.

Table D-4 shows that, except for customers on the DA-RTP rate, customers on the CPP rate do not exhibit flatter load shapes than customers on the other rates. The customers in the DA-RTP group, however, are estimated to have higher peak to off-peak load ratios than customers on the flat rate, where the difference is statistically significant at the 5% level. It is surprising that the load shapes for CPP customers' are not distinctly different than those customers on the flat rate, as indicated by the insignificant coefficients for the CPP variable.

Table D-4
Impacts of Rate Type on Peak to Off-Peak Load Ratios[29]

Variable	Coef.	S.E	t
Constant	**1.159**	0.024	47.91
CPP	0.007	0.017	0.41
DA-RTP	**0.042**	0.018	2.29
PTR	0.013	0.018	0.73
TOU	-0.011	0.018	-0.64
BIHD	0.002	0.012	0.18
AIHD	0.011	0.014	0.84
PCT	-0.012	0.017	-0.71
Bill Protection	0.035	0.022	1.62
Purchase Tech.	0.004	0.020	0.18
Full Education	-0.005	0.029	-0.16
SFSH	0.077	0.074	1.04
MFNS	**-0.176**	0.009	-19.36
MFSH	**-0.105**	0.032	-3.30
Dependent variable: average hourly kW usage during peak hours divided by average hourly kW usage during off-peak hours for non-holiday weekdays from June through August 2010.			

[29] The regression is based upon 5,262 observations, and has an R-squared value of 0.07.

H2e: The CPP rate delivers the best combination of energy efficiency, demand response, and load-shifting benefits.

This hypothesis is designed to embody the previous three hypotheses (H2b, H2c, and H2d). Under the best of circumstances, it would have been difficult to test this joint hypothesis. Initially, the intention was to construct a rank order of the rate treatments based on the differential performance as suggested by the results from the three separate hypothesis tests above. The "best" combination would then be associated with the rate with the smallest average rank. However, the results from above indicate that none of the rate treatments delivers energy efficiency, demand response, or load-shifting benefits at the aggregate level. Since it is impossible to establish a meaningful rank order for these three measures of rate performance, it was also impossible to conduct a meaningful test of hypothesis *H2e*.

H2f: Customers on the IBR rate will experience greater satisfaction than customers on the other rates.

Any test of this hypothesis requires a measure of customer satisfaction, which must be collected through the administration of a survey to all CAP participants and control groups. The specific form of the analysis depends on the nature of the survey questions, which have yet to be designed. Once the data from the survey are available, it is likely that the appropriate test will be an ANOVA-style comparison in which the dependent variable is each customer's self-reported satisfaction score. The independent variables would again account for the several rate and technology treatments. Since these survey results will not be available until the conclusion of the pilot, this hypothesis test will be included in the Phase 2 analysis.

Enabling Technology

All of the hypotheses related to enabling technology are based upon comparisons of data across all treatment cells. As was the case in testing for the effects of the rate treatments, these analyses include variables to account for all of the treatments that customers receive. Therefore, the models tend to be similar (and sometimes identical) to the models used to analyze the effects of the rate treatments.

To test the hypotheses related to enabling technology, it is necessary to develop definitions and measures of *implementation* and *adoption*. For purposes of these analyses, customers are considered to have *implemented* a technology when they install the device so that it is operational. They are deemed to have *adopted* a technology when they make continued use of the technology as measured through web transactions involving the technology. The persistence of adoption is challenging to define because it involves the timing of customers' apparent use of technologies, including lapses in use after initial transactions. Since the measures of adoption must be based on customer's self-reported use of technologies from the 2011 survey, only the tests related to implementation are reported in this Phase 1 analysis.

H3a: The basic in-home display (BIHD) will have a higher implementation rate than other enabling technologies.

This hypothesis test for rates of implementation (i.e., installation) across rate treatments requires the use of a logit regression model in which the dependent variable equals unity if the customer implemented the technology and zero if he/she did not. Again the independent variables account for rate and technology treatments. Because BIHD customers are the omitted technology group, the hypothesis is that the coefficients on the AIHD and PCT variables are negative, indicating a reduced likelihood of implementation for those technologies.

Table D-5 shows the results that compare the implementation rates of the BIHD, AIHD, and PCT technologies. The results confirm the hypothesis, as both the AIHD and PCT coefficients are negative and statistically significant. The negative and statistically significant coefficient on the purchase technology variable is due to the fact that very few customers purchased technology, but the variable is set to unity for all of the customers who were offered the *opportunity* to purchase the technology.

Table D-5
Impacts of Technology on Implementation Rates[30]

Variable	Coef.	S.E	z	Prob
Constant	**-0.750**	0.126	-5.94	32.1%
CPP	0.219	0.150	1.46	37.1%
DA-RTP	0.140	0.159	0.88	58.9%
PTR	-0.023	0.158	-0.15	52.9%
TOU	0.256	0.152	1.69	55.8%
IBR	0.020	0.170	0.12	56.9%
AIHD	**-1.172**	0.100	-11.69	24.0%
PCT	**-0.898**	0.142	-6.31	11.2%
Purchase Tech.	**-2.776**	0.370	-7.5	2.5%
SFSH	-0.089	0.694	-0.13	5.4%
MFNS	**-0.481**	0.089	-5.42	36.1%
MFSH	-0.216	0.302	-0.72	33.3%
Dependent variable: binary choice variable that equals one if the customer implemented the technology and zero otherwise.				

H3b: The BIHD will have a higher adoption rate than other enabling technology.

This test will be conducted in the same way as the test of hypothesis H3a, substituting adoption (installation) for implementation (utilization) as the dependent variable. This test depends on the development of the indicator variable for adoption, which in turn is to be constructed from

[30] The regression is based upon 4,116 observations, and has an R-squared value of 0.08.

survey data that indicates the extent to which customers have used the enabling technologies, as well as other data to describe customer interaction with the technologies. Thus, this test can only be conducted during the Phase 2 analysis.

H3c: A combination of direct and indirect feedback solutions will achieve greater energy efficiency, demand response, and load-shifting benefits than indirect feedback solutions alone.

Three models are required to test this hypothesis. They resemble the models described to test hypotheses H2b, H2c, and H2d. However, they include independent variables in addition to those for rate and technology treatments. Specifically, the additional variables needed describe whether each customer is engaged in direct and/or indirect feedback solutions. Customers are designated as having engaged in direct feedback solutions when they have implemented and adopted BIHD- or AIHD-enabling technologies. Customers are designated as having engaged in indirect feedback solutions when they regularly interact with the OPOWER website. The threshold for regular interaction will be determined following an examination of the data.

Three indicator variables are to be added to the models: one for the use of direct feedback solutions only; one for the use of indirect feedback solutions only; and one for the use of both feedback solutions.[31] For any one of the measures (e.g., energy efficiency that is measured by differences in average usage), the hypothesis is that the coefficient on the indicator variable for the use of both feedback solutions is smaller than the coefficients on the direct- and indirect-only indicator variables.

The results from the three models are to be ranked and summarized using the same method described in the test of hypothesis H2e. A multivariate ANOVA model will be employed here, if it appears appropriate. These tests are to be performed as part of the Phase 2 analysis.

H3d: The advanced in-home display/ programmable controllable thermostat (AIHD/PCT) solution will achieve greater energy efficiency, demand response, and load-shifting benefits than other enabling technology.

There are essentially three separate hypotheses implied in H3d, and each is tested separately. They are tested using models similar to the one discussed at the beginning of this sub-section. The hypothesis in each case is that the coefficient for the AIHD/PCT technology treatment is smaller than the coefficients on the other technology type variables. Because of the small number of PCT installations, the regressions use eWeb as the base technology; but greater benefits from AIHD/PCT, if they exist, may be inferred from the results.

In Table D-6 the three estimated equations show how usage (in average kWh per hour) during all periods, peak periods, and event peak periods depends upon the rate and technology treatments. The model includes both the technology-type indicator variables, as well as variables that are interactions between these variables and whether the customer implemented (i.e., installed) the technology. This facilitates differentiation between the intention to treat and the actual treatment. However, the treatment in this case is not randomly assigned. For example, customers who

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[31] The omitted (*i.e.*, base case) category is the use of neither feedback solution.

implemented BIHD have *higher* usage levels (across all three models) than customers with no technology. It is not possible to distinguish whether this effect is caused by the technology (which seems unlikely) or the fact that customers who chose to implement the technology tended to have higher usage levels (which seems more plausible). Because none of the technology-specific implementation coefficients is negative and significantly different from zero at the 5% level, there is little or no evidence to suggest that enabling technologies lead to lower levels of usage as measured in any of these three different ways.

Table D-6
Impacts of Technology on Electricity Usage[32]

	All Periods			Peak Periods			Event Peaks		
Variable	**Coef.**	**S.E**	**t**	**Coef.**	**S.E**	**t**	**Coef.**	**S.E**	**t**
Constant	**1.502**	0.053	28.17	**1.727**	0.067	25.75	**2.389**	0.099	24.17
CPP	0.009	0.040	0.22	0.043	0.046	0.92	-0.026	0.062	-0.42
DA-RTP	0.048	0.043	1.12	**0.114**	0.052	2.18	0.103	0.070	1.47
PTR	0.011	0.043	0.26	0.047	0.051	0.92	0.015	0.069	0.22
TOU	0.049	0.043	1.13	0.061	0.051	1.19	0.047	0.069	0.67
BIHD	**-0.058**	0.029	-1.96	-0.051	0.038	-1.36	-0.056	0.050	-1.13
AIHD	0.025	0.032	0.77	0.041	0.040	1.02	0.072	0.053	1.35
PCT	0.010	0.040	0.25	-0.013	0.048	-0.27	-0.011	0.064	-0.18
Bill Protection	0.028	0.048	0.59	0.049	0.063	0.79	0.074	0.083	0.88
Purchase Tech.	-0.031	0.049	-0.64	-0.033	0.063	-0.53	-0.056	0.081	-0.69
Full Education	-0.060	0.065	-0.92	-0.098	0.080	-1.22	-0.208	0.114	-1.82
SFSH	0.066	0.196	0.34	0.144	0.257	0.56	-0.062	0.312	-0.20
MFNS	**-0.739**	0.019	-39.39	**-0.966**	0.023	-41.28	**-1.314**	0.031	-41.99
MFSH	**-0.696**	0.080	-8.73	**-0.935**	0.055	-17.14	**-1.293**	0.072	-18.03
BIHD Implement	**0.136**	0.038	3.58	**0.120**	0.049	2.43	**0.160**	0.066	2.41
AIHD Implement	0.044	0.053	0.82	0.002	0.068	0.03	-0.019	0.091	-0.21
PCT Implement	-0.161	0.183	-0.88	-0.203	0.248	-0.82	-0.205	0.326	-0.63
Dependent variables: "All Periods" refers to average hourly kW usage for all days from June through August 2010, "Peak Hours" refers to average hourly kW usage during peak hours on non-holiday weekdays from June through August 2010, and "Event Days" refers to average hourly kW usage during peak hours on event days									

[32] The regressions are based upon 5,262 observations, with R-squared values of approximately 0.20 for all three time periods.

Table D-7 contains the results of a similar test of the effects of rate and technology treatments on the ratios of peak to off-peak usage. Customers who implemented BIHD and AIHD have lower ratios of peak to off-peak usage than customers who do not have enabling technology, and based on the size of the corresponding t-statistics, these differences are statistically significant. As before, it is difficult to know whether these findings are due to effects of the technology or are indicative of the kinds of customers who choose to implement the technology. In addition, the result is somewhat strange because BIHD customers have higher peak-period usage than non-technology customers and AIHD customers' peak-period usage is not different from that of non-technology customers. So the finding seems to indicate that installing these technologies is associated with especially high levels of off-peak usage.

Table D-7
Impacts of Technology on Peak to Off-Peak Usage Ratios[33]

Variable	Coef.	S.E	t
Constant	**1.160**	0.024	47.92
CPP	0.008	0.017	0.46
DA-RTP	**0.042**	0.018	2.33
PTR	0.013	0.018	0.72
TOU	-0.010	0.018	-0.57
BIHD	0.013	0.013	0.94
AIHD	0.017	0.014	1.23
PCT	-0.005	0.018	-0.29
Bill Protection	0.035	0.022	1.61
Purchase Tech.	-0.004	0.020	-0.22
Full Education	-0.005	0.029	-0.18
SFSH	0.077	0.073	1.05
MFNS	**-0.178**	0.009	-19.48
MFSH	**-0.106**	0.032	-3.34
BIHD Implement	**-0.034**	0.016	-2.21
AIHD Implement	**-0.044**	0.021	-2.08
PCT Implement	-0.006	0.086	-0.06
Dependent variable: average hourly kW usage during peak hours divided by average hourly kW usage during off-peak hours for non-holiday weekdays from June through August 2010.			

[33] The regression is based upon 5,262 observations, with an R-squared of 0.07.

H3e: The AIHD/PCT solution in combination with the CPP rate will achieve greater energy efficiency, demand response, and load-shifting benefits than other enabling technology and pricing plan combinations.

The hypothesis to be tested is that usage by customers in cell D4 is lower than usage by customers in other cells. **Error! Reference source not found.** contains the results of statistical comparisons of the usage during three different time periods for of customers in the different cells. These comparisons are all relative to the control group in cell F3 (which contains customers on the flat rate who have an AMI meter, and have received basic AMI education) with SFNS housing. Therefore, the Constant row denotes values for customers in cell F3 with SFNS housing; for example, the average hourly consumption of SFNS customers in cell F3 in all periods equals 1.503 kWh. Hourly consumption for customers in each other cell equals the constant coefficient plus the coefficient on the appropriate indicator or dummy variable. For example, the average hourly consumption of customers in cell D1a in all periods equals 1.446 kWh (= 1.503 - 0.057).

Table D-8
Usage of Cells Relative to Cell F3[34]

	All Periods			Peak Periods			Event Peaks		
Cell	**Coef.**	**S.E**	**t**	**Coef.**	**S.E**	**T**	**Coef.**	**S.E**	**t**
Constant	**1.503**	0.053	28.18	**1.728**	0.067	25.75	**2.391**	0.099	24.17
D1a	-0.057	0.062	-0.91	-0.078	0.079	-0.99	**-0.244**	0.113	-2.16
D1b	0.052	0.080	0.65	0.086	0.105	0.81	-0.062	0.147	-0.42
D2	-0.090	0.064	-1.41	-0.098	0.081	-1.21	**-0.307**	0.114	-2.68
D3	0.000	0.066	-0.01	0.019	0.083	0.23	-0.120	0.119	-1.01
D4	-0.055	0.065	-0.83	-0.087	0.079	-1.09	**-0.262**	0.114	-2.31
D5	0.009	0.079	0.11	0.017	0.099	0.17	-0.110	0.135	-0.81
D6	-0.105	0.064	-1.65	-0.109	0.081	-1.34	**-0.250**	0.117	-2.13
D7	-0.030	0.081	-0.37	-0.016	0.106	-0.15	-0.117	0.146	-0.80
D8	0.004	0.073	0.06	-0.035	0.091	-0.38	-0.192	0.130	-1.48
F5	-0.079	0.079	-1.00	-0.106	0.098	-1.08	**-0.275**	0.134	-2.05
F6	-0.092	0.070	-1.32	-0.121	0.088	-1.38	-0.199	0.127	-1.56
F7	0.009	0.092	0.10	-0.037	0.099	-0.37	-0.096	0.141	-0.68
L1a	-0.031	0.076	-0.41	-0.005	0.096	-0.05	-0.100	0.133	-0.75
L1b	-0.049	0.077	-0.64	-0.016	0.097	-0.17	-0.121	0.136	-0.89
L2	0.000	0.065	0.01	0.040	0.085	0.47	-0.098	0.119	-0.82
L3	0.050	0.076	0.66	0.084	0.098	0.85	0.021	0.140	0.15

[34] The regressions are all based upon 5,262 observations, and all have R-squared values of approximately 0.20.

	All Periods			Peak Periods			Event Peaks		
Cell	**Coef.**	**S.E**	**t**	**Coef.**	**S.E**	**T**	**Coef.**	**S.E**	**t**
L4	-0.007	0.067	-0.11	-0.017	0.087	-0.19	-0.151	0.124	-1.22
L5a	0.022	0.066	0.34	-0.008	0.083	-0.10	-0.101	0.119	-0.85
L5b	-0.108	0.074	-1.45	-0.127	0.094	-1.35	-0.244	0.133	-1.83
L6a	-0.083	0.074	-1.12	-0.101	0.095	-1.07	-0.242	0.132	-1.84
L6b	-0.006	0.079	-0.07	-0.020	0.102	-0.20	-0.172	0.134	-1.29
SFSH	0.073	0.198	0.37	0.153	0.261	0.59	-0.047	0.318	-0.15
MFNS	**-0.744**	0.019	-39.86	**-0.970**	0.023	-41.60	**-1.318**	0.031	-42.31
MFSH	**-0.693**	0.080	-8.68	**-0.931**	0.055	-17.04	**-1.287**	0.072	-17.84
Dependent variables: "All Periods" refers to average hourly kW usage for all days from June through August 2010, "Peak Hours" refers to average hourly kW usage during peak hours on non-holiday weekdays from June through August 2010, and "Event Days" refers to average hourly kW usage during peak hours on event days									

Based on the very small absolute values of the t-statistics on the coefficients for each treatment cell, it is apparent from Table D-8, that by any of the three measures, usage differs from that of the control group F3 (where customers pay a flat rate for electricity) *in only a handful* of treatment cells. There are several instances where event-hour usage by CPP and PTR customers is significantly different than that of customers in the control group. Specifically, during peak periods on event days, customers in F3 (the control group facing a flat rate) consume more electricity than customers in three of the five CPP cells (D1a, D2, and D4) and one of the PTR cells (D6). However, a particularly odd result is that the customers in cell F5 (flat rate customers with e-Web and education) also consume less electricity on average during peak periods on event days than the control group F3, and they differ from the other flat rate customers in the control group only in the fact they received additional education.

These exceptions provide some important support for this hypothesis; but in general, the evidence that usage by customers in cell D4 is lower than usage by customers in other cells is rather weak.

Table D-9 reports the results for the regression to explain how the ratios of peak to off-peak usage differ by treatment cell. Based on the t-statistics, which, with one exception, are all below 2.0 in absolute value indicate that ratios of peak to off-peak usage in all treatment cells are statistically indistinguishable from the average for customers in group F3, the control customers that pay a flat rate.

Table D-9
Peak to Off-Peak Usage Ratios of Cells Relative to Cell F3[35]

Cell	Coef.	S.E	t
Constant	**1.159**	0.024	47.86
D1a	-0.009	0.028	-0.32
D1b	0.031	0.035	0.89
D2	0.001	0.030	0.05
D3	0.022	0.029	0.76
D4	-0.003	0.030	-0.09
D5	0.016	0.034	0.47
D6	0.012	0.029	0.41
D7	0.027	0.036	0.77
D8	-0.022	0.033	-0.68
F5	0.032	0.039	0.81
F6	-0.016	0.030	-0.51
F7	-0.013	0.034	-0.37
L1a	0.013	0.033	0.39
L1b	**0.077**	0.037	2.1
L2	0.049	0.030	1.61
L3	0.046	0.034	1.34
L4	-0.014	0.033	-0.42
L5a	-0.016	0.028	-0.56
L5b	-0.006	0.033	-0.18
L6a	-0.003	0.033	-0.08
L6b	-0.005	0.034	-0.16
SFSH	0.074	0.073	1.01
MFNS	**-0.176**	0.009	-19.32
MFSH	**-0.106**	0.032	-3.34
Dependent variable: average hourly kW usage during peak hours divided by average hourly kW usage during off-peak hours for non-holiday weekdays from June through August 2010.			

[35] The regression is based upon 3,219 observations, with an R-squared of 0.07.

H3f: Customers activating a BIHD will experience greater satisfaction than customers who have received and activated other enabling technology.

As part of the Phase 2 analysis, this hypothesis test will be conducted using the model developed to test hypothesis H2f. Satisfaction will be measured using data collected from the survey administered to CAP participants. The hypothesis is that the coefficient for BIHD will be higher than the coefficients for the other technology types.

Enabling Technology Acquisition

All of the hypotheses regarding the acquisition of enabling technologies are based upon comparisons of data within two cells:

- Customer groups L5a and L5b, and
- Customer groups L6a and L6b

Hypotheses H4b, H4c, and H4d suggest that customers who willingly purchase enabling technology, albeit it at a subsidized cost, will take actions that differ from those who were offered the technology at no cost.[36]

H4a: The acquisition rate of free enabling technology will exceed that of purchased enabling technology.[37]

Customers in groups L5a and L6a were given enabling technologies at no cost. Customers in groups L5b and L6b, who were otherwise identical to L5a and L6a customers, respectively, were offered enabling technologies for purchase. Table D-10 provides data on how many customers in each group were offered enabling technologies, how many acquired those technologies, and how many implemented the technologies. It also provides the acquisition rates (number acquired divided by number offered, expressed as a percentage) and implementation rates (number implemented divided by number acquired, expressed as a percentage).

The acquisition rate for enabling technology that is provided at no cost is 100% because the CAP project provided customers with this technology without the customer having to request it. By contrast, of the 416 customers in groups L5b and L6b who were offered technology for purchase, only 9 (or 2%) accepted the purchase offer, albeit at a heavily subsidized price. While the numbers of customers purchasing the technologies were too small to support formal ANOVA tests, these descriptive data do support the assertion that only a small fraction of customers are likely to purchase enabling technology. However, because customers who obtained the technology free of charge did so without requesting the technology, there is no way to know what proportion of these customers would have actually requested the technology at no cost.

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[36] One sub-set of customers was offered the opportunity to purchase the BIHD for $42 and another was offered the AIHD for $84.

[37] Because all customers who were given the BIHD and AIHD will be coded as having acquired the technology, this hypothesis is going to be true by definition unless all customers who were offered the opportunity to purchase the technology did purchase it.

Table D-10
Acquisition and Implementation of Free and Purchased Technology

	Numbers			Rates	
	Offer	Acquire	Implement	Acquire	Implement
For Free					
L5a	485	485	163	100%	34%
L6a	205	205	26	100%	13%
For Purchase					
L5b	211	5	4	2%	80%
L6b	205	4	4	2%	100%

H4b: The implementation rate of purchased enabling technology will exceed that of free enabling technology.

Table D-10 also contains data that suggest that customers who purchased enabling technologies also implemented the technology at much higher rates than did customers who were given the technologies at no cost (80% to 100% versus 13% to 34%). On the one hand, this is a plausible result; people who pay for something are more likely, but not always, to place a higher value on it than people who receive it at no cost. On the other hand, the rates of implementation in Table D-10 for those receiving the technology at no cost may well understate the rates of implementation that would be experienced if customers had been required to at least request the technology. In summary, the available evidence supports the hypothesis; but the evidence would be stronger if: a) customers given the enabling technology were required to request the technology; and b) there was a large population of customers who were offered the technology for purchase so that the "for purchase" acquisition and implementation rates were more statistically meaningful.

H4c: The adoption rate of purchased enabling technology will exceed that of free enabling technology.

The analytical considerations for the test of this hypothesis are identical to those described for the test of H4b, except that this hypothesis pertains to adoption rather than implementation. The tests will, therefore, also be conducted after survey data become available, and the results will be in the Phase 2 report.

H4d: Purchased enabling technology will achieve greater energy efficiency, demand response, and load-shifting benefits than free enabling technology.

To test this hypothesis, we restrict our analyses to include only customers in treatment cells L5 and L6, which were split so that some customers were given the technology while others were offered it for purchase. Viewed from one perspective, this hypothesis could be viewed as a joint hypothesis related to the four important aspects of electricity consumption discussed throughout this report. However, rather than treat the joint nature of the hypothesis directly, we specify four regression models, the dependent variable differs for each (e.g. consumption across all hours, consumption on peak, consumption on peak for event days, and the ratio of peak to off-peak consumption). The same independent variables are included in each of the four separate regression models, and estimation results for the two independent variables of most interest are reported below: one variable takes on the value of unity if the customer had the opportunity to purchase the technology (this is the variable of interest), and it is zero otherwise. The other variable relates to the type of technology that was either given or offered for purchase. The variable takes on the value of unity if the technology is AIHD, and a value of zero if not. Thus, the control group for these regressions includes customers who received BIHD at no cost.[38]

Table **D-11** contains the results of these four regressions. Because of their simplicity each regression is reported in a row of the table, rather than in a column as is the case elsewhere in this appendix. Again, while the negative signs on the coefficient for the purchase variable in three of the four regressions are as expected, the t-ratios are extremely small in absolute value, which indicate that there are no significant relationships between these four important measures of usage and whether the customer was given the technology or was given the opportunity to purchase it.

Table D-11
Usage Comparisons by Method of Obtaining Technology[39]

	Constant			AIHD			Purchase Technology		
Period	**Coef.**	**S.E**	**t**	**Coef.**	**S.E**	**t**	**Coef.**	**S.E**	**t**
All Periods	**1.475**	0.045	32.6	-0.019	0.051	-0.38	-0.044	0.051	-0.85
Peak	**1.662**	0.056	29.51	-0.011	0.065	-0.17	-0.034	0.065	-0.53
Event Peak	**2.225**	0.077	28.85	-0.053	0.085	-0.63	-0.053	0.085	-0.62
Peak to Off-Peak Ratio	**1.136**	0.015	73.72	0.008	0.021	0.4	0.005	0.021	0.26

Dependent variables: "All Periods" refers to average hourly kW usage for all days from June through August 2010, "Peak" refers to average hourly kW usage during peak hours on non-holiday weekdays from June through August 2010, "Event Peak" refers to average hourly kW usage during peak hours on event days, and "Peak to Off-Peak Ratio" refers to average hourly kW usage during peak hours divided by average hourly kW usage during off-peak hours for non-holiday weekdays from June through August 2010.

[38] More specifically, the control group includes customers who received BIHD at no cost and have SFNS housing. Variables indicating housing type were also included in the regression and are reported in Appendix E.

[39] The regressions are all based upon 1,002 observations, and have R-squared values from 0.05 to 0.16. See Appendix E for additional details.

Bill Protection

There are three hypotheses in the analysis plan that relate to bill protection. These hypothesis tests are based upon comparisons of data within two cells:

- Customer groups D1a and D1b (customers on the CPP rate, with e-Web technology, where customers in sub-group “a” were not informed of bill protection, while those in sub-group “b” were); and
- Customer groups L1a and L1b (customers on the DA-RTP rate, with e-Web technology, where customers in sub-group “a” were not informed of bill protection, while those in sub-group “b” were).

H5a: The adoption rate of a dynamic pricing plan will be greater when bill protection is offered than when it is not offered.

This hypothesis was tested using a logit model. The dependent variable takes on a value of unity if the customer opted out of the pilot, and a value of zero otherwise. The independent variables include indicators for each of the rate treatments, housing types, and an indicator variable distinguishing customers who have been notified of bill protection. Only customers in cells D1 (CPP) and L1 (DA-RTP) are included in the sample. The hypothesis being tested is that the coefficient on the bill protection variable is negative.

Table D-12 shows the estimated impact of bill protection on opt-out rates. The coefficient for the constant implies an opt-out rate of 3.58% for CPP customers with SFNS housing who were not informed of bill protection. The opt-out rate for DA-RTP customers is calculated from the sum of the constant term and the coefficient on the DA-RTP indicator variable. The impact of bill protection is implied by the coefficient on dummy variable for bill protection. The very small z-statistic indicates that bill protection does not significantly affect opt-out rates.

Table D-12
Impact of Bill Protection on Opt-Out Rates[40]

Variable	Coef.	S.E	z	Opt Outs
Constant	**-3.293**	0.282	-11.69	3.58%
DA-RTP	-0.800	0.471	-1.7	1.64%
Bill Protection	0.223	0.398	0.56	4.44%
SFSH	(omitted)			
MFNS	-0.621	0.442	-1.4	1.96%
MFSH	(omitted)			
Dependent variable: binary choice variable that equals one if the customer opted out of the pilot program and zero otherwise.				

[40] The regression is based upon 1,092 observations, with a Psuedo R-squared of 0.02. See Appendix E for additional details.

H5b: Customers without bill protection will achieve greater energy efficiency, demand response, and load-shifting benefits than customers with bill protection.

Since this hypothesis embodies the several measures of performance in terms of load reduction, etc. four separate hypothesis tests are specified. The dependent variable for each of them is one of the four important measures of customer usage. Furthermore, to test these hypotheses, we restrict our analyses to include only customers in cells D1 and L1, which were split so that some customers were notified of bill protection and others were not. The regression models include two independent variables of particular interest which are included in Table D-13. One variable takes on a value of unity if the customer was notified of bill protection and a value of zero otherwise. This is the variable of interest. The other variable takes on a value of unity if the customer is in the CPP treatment and a value of zero otherwise. Thus, the treatment group for the DA-RTP rate without bill protection serves as the control group for this regression analysis.[41]

Table D-13 contains the results for these four separate hypothesis tests. Since the t-statistics associated with the estimated coefficients on bill protection in three of the models are small in absolute value, there is no evidence that there is any significant difference in these three measures of electricity consumption between customers who were notified of bill protection and those who were not notified. However, bill protection does appear to have a positive and significant effect on the peak to off-peak ratio.

Table D-13
Usage Comparisons by Notification of Bill Protection[42]

	Constant			CPP			Bill Protection		
Period	**Coef.**	**S.E**	**t**	**Coef.**	**S.E**	**t**	**Coef.**	**S.E**	**t**
All Periods	**1.435**	0.056	25.64	0.024	0.051	0.46	0.056	0.052	1.07
Peak	**1.683**	0.072	23.27	-0.006	0.066	-0.09	0.090	0.068	1.32
Event Peak	**2.233**	0.094	23.68	-0.064	0.087	-0.74	0.096	0.090	1.06
Peak to Off-Peak Ratio	**1.182**	0.022	54.34	-0.032	0.022	-1.44	**0.051**	0.023	2.22

Dependent variables: "All Periods" refers to average hourly kW usage for all days from June through August 2010, "Peak" refers to average hourly kW usage during peak hours on non-holiday weekdays from June through August 2010, "Event Peak" refers to average hourly kW usage during peak hours on event days, and "Peak to Off-Peak Ratio" refers to average hourly kW usage during peak hours divided by average hourly kW usage during off-peak hours for non-holiday weekdays from June through August 2010.

[41] More specifically, the control group includes DA-RTP customers without bill protection who have SFNS housing. Variables indicating housing type were also included in the regression and are reported in Appendix E.

[42] The regressions are all based upon 872 observations, and all have R-squared values between 0.09 and 0.23. See Appendix E for additional details.

H5c: Customers with bill protection will experience greater satisfaction than customers without bill protection.

This hypothesis test will be conducted using the model developed to test hypothesis H2f. An indicator variable for the notification of bill protection will be included, and the hypothesis is that the coefficient on this variable is positive.[43] Since this test requires data that will be collected from the survey, it will be performed as part of the Phase 2 analysis.

Before moving on, it is important to note that the results of these hypotheses regarding bill protection should be interpreted with some caution. It is our understanding that throughout the pilot, ComEd has operated under an unstated policy to make all customers whole at the end of the pilot. Thus, there is some chance that ComEd's intention in this regard may have been revealed (accidentally or intentionally) during the course of the pilot to customers other than those in cells D1b and L1b, who were explicitly notified that they will receive bill protection. There are some data indicating which customers were told of the bill protection when they attempted to opt out of the program; but unless they are asked in the exit survey, we will never know whether some other customers may have been notified informally (e.g., by a neighbor who was told of the bill protection by ComEd). If this kind of information is collected in the survey, we may well be able to refine these hypothesis tests in Phase 2 of the analysis.

Customer Education

For this group of hypotheses, customers in treatment cell F3 received Basic AMI Education. Customers in this treatment cell received awareness education about the smart meter system and the flat rate they are charged for electricity (disseminated through materials that came with meter installation and a Rate Notification Letter). Customers in this group have access to Energy Tips on the OPOWER website, as well as access to the hourly data on the website.

Customers in all other treatment cells received the Education treatment. It involves Basic AMI Education *plus* detailed rate education, access to the Customer Education Package (by mail or online), a monthly OPOWER report, IHD videos (available online), an IHD user manual, and a quick-start guide for applicable cells. All customers who do not pay a flat rate for electricity received this education.

Customers in cell F1 are from ComEd's load research sample, and these customers are not involved in the pilot. Customers in this sample received no education. Customers in cell F2 are those who do not have an AMI meter, but they did receive education. They pay the flat rate for electricity, and they reside outside of the AMI footprint.

H6a: Customers receiving customer education will achieve greater energy efficiency, demand response, and load-shifting benefits than customers who do not receive customer education.

The tests of this hypothesis are based on customers only from cells F1 and F2. As in some other cases, this is really a joint hypothesis, but each piece of it is tested separately. Thus, four separate

[43] The omitted (*i.e.*, "base case") category is customers who were not notified of bill protection.

regression models are specified, one for which the dependent variable is one of the four measures of electricity consumption focused on throughout this analysis. The independent variables are an indicator variable that is equal to unity if the customer received education (i.e., the customer is in cell F2) and zero if the customer did not (i.e., the customer is in cell F1) and indicator variables for housing type. The hypothesis is that the coefficient on the F2 variable will be negative in each model.

This is a direct test of the effect of education on customer behavior, absent any additional influences from the dynamic rate treatments, the AMI meter, or any treatments for enabling technologies. It is impossible to include customers from any of the rate treatment groups in this test for the effect of education because all customers in treatments not paying the flat rate received customer education.

Table D-14 presents the results for the tests related to energy efficiency and demand response. The coefficients for the constant terms in these three equations represent the average kWh consumption for customers in cell F1 with SFNS housing for the three respective periods of interest. The coefficients for the F2 dummy variables represent the differences in average kWh consumption between customers in groups F1 and F2. While the negative signs on these coefficients are as expected, their t-statistics are too small in absolute value for these differences to be statistically significant for any of the three periods.

Table D-14
Impact of Customer Education on Usage [44]

	All Periods			Peak Periods			Event Peaks		
Variable	**Coef.**	**S.E**	**t**	**Coef.**	**S.E**	**t**	**Coef.**	**S.E**	**t**
Constant	**2.187**	0.131	16.69	**2.715**	0.171	15.84	**3.552**	0.224	15.83
F2	-0.040	0.157	-0.25	-0.044	0.193	-0.23	-0.025	0.239	-0.1
SFSH	**0.715**	0.251	2.85	**0.717**	0.321	2.23	0.548	0.379	1.44
MFNS	**-0.586**	0.202	-2.91	**-0.895**	0.254	-3.52	**-1.291**	0.334	-3.87
MFSH	-0.326	0.196	-1.66	**-0.749**	0.244	-3.08	**-1.179**	0.308	-3.83

Dependent variables: “All Periods” refers to average hourly kW usage for all days from June through August 2010, “Peak Periods” refers to average hourly kW usage during peak hours on non-holiday weekdays from June through August 2010, and “Event Peaks” refers to average hourly kW usage during peak hours on event days.

Table D-15 presents the results for the equation for the version of this hypothesis test related to load-shifting. The constant term shows the average ratio of peak to off-peak usage for customers in group F1 with SFNS housing, while the coefficient for the F2 dummy variable reflects the difference in the average ratio of peak to off-peak electricity consumption between the customers in groups F1 and F2. The positive sign on this coefficient is probably not what one would expect,

[44] The regressions are based upon 582 observations, with R-squared values of approximately 0.05. See Appendix E for additional details.

but again the t-statistic is quite small, which implies that there is no statistically significant difference in the ratios of peak to off-peak electricity consumption between these two groups. The evidence does not support hypothesis H6a.

Table D-15
Impact of Customer Education on Peak to Off-Peak Usage Ratios [45]

Variable	Coef.	S.E	T
Constant	**1.291**	0.029	45.08
F2	0.028	0.031	0.89
SFSH	-0.073	0.039	-1.89
MFNS	**-0.151**	0.040	-3.75
MFSH	**-0.183**	0.038	-4.84
Dependent variable: average hourly kW usage during peak hours divided by average hourly kW usage during off-peak hours for non-holiday weekdays from June through August 2010.			

H6b: Customers who receive customer education along with an AMI-enabled, non-flat rate and enabling technology will achieve greater energy efficiency, demand response, and load-shifting benefits than customers who are offered a flat rate and Basic AMI Education.

As was the case for the previous hypothesis, this is really a joint hypothesis, but each piece of it is tested separately. Thus, four separate regression models are specified, one for which the dependent variable is one of the four measures of electricity consumption focused on throughout this analysis. To test this hypothesis, one must compare customers in the control group who pay a flat rate and have only eWeb access, cell F3, with customers who do not pay a flat or IBR rate for electricity and who have an AMI-enabled, enabling technology (cells D2, D3, D4, D6, D7, D8, L2, L3, L5a, and L6a). The independent variables in each of these regression equations include indicators for housing type and an indicator variable that equals unity if the customer is in cell F3 (i.e., pay a flat rate and has only basic AMI education), and zero otherwise. The hypothesis is that the coefficient on the F3 variable is positive in each model.

Table D-16 presents the results for the three equations that relate to energy efficiency and demand response. The constant coefficients represent average hourly kWh usage for all customers in treatment groups where customers do no pay a flat or IBR rate, but do have an AMI-enabled enabling technology and SFNS housing. The coefficients for the dummy variable associated with the F3 variable reflect the differences in the respective measures of electricity usage between F3 and all other treatment groups mentioned above. The positive signs on these coefficients are again as expected, but the small t-statistics suggest that this effect is not statistically significant for any of the three periods.

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[45] The regression is based upon 582 observations, with an R-squared of 0.05. See Appendix E for additional details.

Table D-16
Impact of Technology and Customer Education Usage[46]

	All Periods			Peak Periods			Event Peaks		
Variable	**Coef.**	**S.E**	**t**	**Coef.**	**S.E**	**t**	**Coef.**	**S.E**	**t**
Constant	**1.472**	0.019	79.29	**1.690**	0.024	70.03	**2.214**	0.032	69.01
F3	0.035	0.054	0.64	0.039	0.068	0.58	0.179	0.100	1.79
SFSH	-0.027	0.236	-0.11	0.017	0.297	0.06	-0.148	0.381	-0.39
MFNS	**-0.749**	0.023	-32.23	**-0.973**	0.029	-33.55	**-1.327**	0.039	-34.33
MFSH	**-0.761**	0.057	-13.34	**-0.943**	0.068	-13.94	**-1.273**	0.090	-14.13
Dependent variables: "All Periods" refers to average hourly kW usage for all days from June through August 2010, "Peak Periods" refers to average hourly kW usage during peak hours on non-holiday weekdays from June through August 2010, and "Event Peaks" refers to average hourly kW usage during peak hours on event days.									

Table D-17 presents the results for the equation that tests the version of this hypothesis test related to load-shifting. The constant term represents the average ratio of peak to off-peak usage for all customers in treatment groups where customers do not pay a flat or IBR rate, but do have an AMI-enabled enabling technology and SFNS housing. The coefficient on the dummy variable for F3 is a reflection of the difference in average load ratios between customers in the F3 group and customers in the other treatment groups. In this case, the sign on this coefficient is not as expected, but because the absolute value of the t-statistic is so small, there is no statistically significant difference between the load ratios.

Table D-17
Impact of Technology and Customer Education on Peak to Off-Peak Usage Ratios [47]

Variable	Coef.	S.E	t
Constant	**1.170**	0.007	160.02
F3	-0.009	0.025	-0.37
SFSH	0.051	0.079	0.65
MFNS	**-0.183**	0.011	-16.46
MFSH	-0.079	0.043	-1.85
Dependent variable: average hourly kW usage during peak hours divided by average hourly kW usage during off-peak hours for non-holiday weekdays from June through August 2010.			

[46] The regressions are based upon 3,435 observations, with R-squared values of approximately 0.20. See Appendix E for additional details.
[47] The regression is based upon 3,435 observations, with an R-squared of 0.07. See Appendix E for additional details.

In summary, none of the evidence from the four regression equations supports hypothesis H6b.[48]

H6c: Customers who receive customer education along with an AMI-enabled, non-flat rate and enabling technology will achieve greater energy efficiency, demand response, and load-shifting benefits than customers who receive customer education, a flat rate, and enabling technology.

As in the previous hypothesis, this is really a joint hypothesis, but each piece of it is tested separately. Thus, four separate regression models are specified, one for which the dependent variable is one of the four measures of electricity consumption focused on throughout this analysis. To test this hypothesis, one must compare customers who face the flat rate and have an AMI-enabled enabling technology (treatment cells F6 and F7) with customers who have an AMI-enabled enabling technology but who do not pay a flat or IBR rate (treatment cells D2, D3, D4, D6, D7, D8, L2, L3, L5a, and L6a). The independent variables in each of these regression equations include indicators for housing type and an indicator variable that equals unity if the customer is in cell F6 or F7 (i.e., pays a flat rate, has received education, and has enabling technology). The hypothesis is that the coefficient on the F6|F7 variable in each model is positive.

Table D-18 presents the results for the three equations related to measures of energy efficiency and demand response. The constant coefficients represent average hourly kWh usage for the treatment groups where customers do not face the flat rate, but are AMI-enabled, have enabling technology, and have SFNS housing. The coefficients on the F6| F7 dummy variables reflect the differences in usage between customers in the combined F6| F7 group and customers in the other groups. In two of the equations, the negative signs on the coefficients are not expected, but again, all three t-statistics on these coefficients are small in absolute value thus implying that the differences in usage between the two groups are not statistically significant for any of the three periods.

Table D-18
Impact of Technology and Customer Education on Usage[49]

	All Periods			Peak Periods			Event Peaks		
Variable	**Coef.**	**S.E**	**t**	**Coef.**	**S.E**	**t**	**Coef.**	**S.E**	**t**
Constant	**1.473**	0.018	80.08	**1.691**	0.024	71.4	**2.218**	0.031	70.4
F6lF7	-0.014	0.044	-0.33	-0.046	0.049	-0.94	0.024	0.068	0.36
SFSH	-0.027	0.236	-0.12	0.016	0.297	0.05	-0.151	0.381	-0.4
MFNS	**-0.757**	0.022	-33.89	**-0.976**	0.028	-35.07	**-1.335**	0.037	-35.87
MFSH	**-0.660**	0.129	-5.1	**-0.940**	0.071	-13.18	**-1.295**	0.088	-14.67
Dependent variables: "All Periods" refers to average hourly kW usage for all days from June through August 2010, "Peak Periods" refers to average hourly kW usage during peak hours on non-holiday weekdays from June through August 2010, and "Event Peaks" refers to average hourly kW usage during peak hours on event days.									

[48] Tests that were limited to single-family non-space heating customers found similar results.
[49] The regressions are based upon 3,689 observations, with R-squared values of approximately 0.19. See Appendix E for additional details.

Table D-19 presents the results for the equation that tests the version of this hypothesis related to load-shifting. The constant term shows the ratio of average peak to off-peak usage for the customer groups not paying the flat rate, but who are AMI-enabled, have enabling technology, and have SFNS housing. The coefficient on the dummy variable for the customers in the combined group F6|F7 reflects the difference in load ratios between the F6|F7 group and the other groups. While the sign is not as expected, the small absolute value of the t-statistic implies that there is no significant difference in the load ratios between these two groups.

Table D-19
Impact of Technology and Customer Education on Peak to Off-Peak Usage Ratios [50]

Variable	Coef.	S.E	t
Constant	**1.168**	0.007	162.03
F6|F7	-0.023	0.016	-1.45
SFSH	0.053	0.079	0.67
MFNS	**-0.177**	0.011	-16.46
MFSH	**-0.106**	0.040	-2.62
Dependent variable: average hourly kW usage during peak hours divided by average hourly kW usage during off-peak hours for non-holiday weekdays from June through August 2010.			

In summary, none of the evidence from any of the four tests supports hypothesis H6c.[51]

H6d: Customers who receive customer education will experience greater satisfaction than customers without customer education.

As with the other hypotheses that are related to customer satisfaction, this test requires data that will be collected from the customer survey to be administered near the end of the pilot. Thus, the results of the test will appear in the Phase 2 report to be completed later in the year. This hypothesis test will be conducted using the model developed to test hypothesis H2f. An indicator variable equal to unity will be specified for customers who receive education and a value of zero otherwise. A separate variable will be specified and will be equal to unity for customers who receive no education. Based on this specification, it will be the group of customers who receive basic AMI education that will constitute the omitted, control group. The hypothesis is that the coefficients on the education variables are positive.

[50] The regression is based upon 3,689 observations, with an R-squared of 0.07. See Appendix E for additional details.
[51] Tests that were limited to single-family non-space heating customers found similar results.

Customer Experience – Observable Steps

The tests of hypotheses related to customer experience involve a number of observable steps that customers may take during participation in the CAP pilot. The following list contains examples of these observable steps:

- Returned Survey A
  - Notification Preference Updated on survey with one or more of the following: email, text, and/or phone
  - Customer Education Package Requested on the survey
- Requested Customer Education Package via RNL postcard
- Created a Web Account
- Called to schedule an OpenPeak, or to purchase a Tendril or OpenPeak
- Activated a Tendril or OpenPeak
- Called ComEd call center
- Completed exit survey at the end of the study.

Throughout the remainder of the pilot, we will continue to collect the necessary data to construct metrics from the measurement and validation database to represent the number and timing of the above observable steps.

H7a: Customers who engage in small, observable steps will achieve greater energy efficiency, demand response, and load-shifting benefits than customers who do not engage in those steps.

As in the previous hypothesis, this is really a joint hypothesis, but each piece of it is tested separately. Thus, four separate regression models are specified, one for which the dependent variable is one of the four measures of electricity consumption focused on throughout this analysis. Furthermore, this hypothesis test will build upon the test of hypothesis H3d by including an indicator variable that equals unity for customers who have engaged in small, observable steps, and a value of zero otherwise. We will need to exercise some judgment based on an examination of the data to determine the specific conditions under which this variable will be assigned a value of unity. The hypothesis is that the coefficient on this indicator variable for observable steps is negative.

Since the tests of this hypothesis depend on data from the customer survey, the results of the test will be reported in the Phase 2 report to be completed later this year.

Customer Experience – Opt-Out Enrollment

Since CAP involves only an *opt-out* design, the following four hypotheses, designed to test differences between various results for *opt-out* versus *opt-in* rate designs, will be developed through comparisons of data from reports by other utilities on the performance of their *opt-in* and *opt-out* pilot program. Key points for comparison include: differences in customer participation rates, changes in energy usage, and customers' satisfaction with the various rates.

Analyses of these hypotheses are awaiting data regarding other utilities' experiences, and the results will be reported in the Phase 2 report to be completed later this year.

H7b: An opt-out strategy will result in a higher enrollment percentage than an opt-in strategy.

This analysis will involve comparisons of ComEd's percentages of enrolled customers (less drop-outs) to other utilities' reported opt-in and opt-out customer enrollment percentages (e.g., the number of customer contacts that were required to achieve required sample sizes).

H7c: An opt-out strategy will result in greater adoption of new pricing plans and enabling technology than an opt-in strategy.

Using the definition of rate adoption as the lack of opt-out actions, the analysis will compare other utilities' reported rates of adoption of new pricing plans and enabling technology, differentiated by opt-in and opt-out strategies.

H7d: An opt-out strategy will result in greater energy efficiency, demand response, and load-shifting benefits than an opt-in strategy.

The analysis will compare the four metrics of energy usage emphasized throughout this Phase 1 analysis of the CAP, with similar measures from other utilities, distinguished by their opt-out and opt-in designs. There will be controls for the use of enabling technology.

H7e: Customer satisfaction with an opt-out strategy will not be significantly different than satisfaction with an opt-in strategy.

The analysis will compare reported customer satisfaction results based on surveys conducted near the end of the programs.

Customer Experience – Comparisons

The following set of hypotheses relate to suggested changes in customer behavior that are based on information about rate comparisons and normative comparisons that customers experience and receive in particular months or over a series of months.[52] The analysis of rate comparisons must: a) distinguish among losers according to the relative sizes of their losses (i.e., bill increases), and among winners according to the relative sizes of their gains (i.e., bill reductions); b) account for when losses or gains are made known to customers; and c) address cases in which a customer sees alternating monthly losses and gains.

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[52] "Rate comparisons" show each customer both their actual monthly CAP bill and what their bill would have been under the flat rate. "Normative comparisons" show each customer their own usage level relative to a comparison group of their "neighbors."

Analyses of these hypotheses require an examination of data over many billing cycles. Consequently, these analyses can be performed only after data from the entire year of the period of the CAP pilot are available. The results will be presented in the Phase 2 report.

H7f: Customers whose rate comparison shows a monthly loss will change their behavior in subsequent months to minimize that loss.

This hypothesis can be tested using results derived from our estimated customer-specific demand models. These demand models allow us to estimate elasticities of substitution between peak and off-peak electricity by day, and these can be averaged or otherwise combined for any specified rate type and time period. In this way, these estimated elasticities of substitution can be the dependent variable in a second-stage model. For example, the dependent variable in one of several second-stage models could be average monthly customer-level elasticities of substitution (where the month corresponds to each customer's billing month). The independent variables that are likely to be associated with changes in customer's elasticities of substitution may well include those related to weather, customer fixed effects (which account for customer-specific factors that do not change during the sample timeframe, and therefore include rate type and technology type), time-based indicator variables (e.g., indicating month of the year), and a variable indicating whether the previous billing month represented a loss.

In conducting these tests, it is likely that a loss will be defined as a month in which the customer received a higher bill on its CAP rate that he/she would have received on its standard rate. Loss categories may also be introduced that separate small losses from larger losses (e.g., less than 10% vs. 10% or more). The hypothesis is that the coefficient on the loss variable will be positive, indicating a higher elasticity of substitution for customers who previously experienced a loss.

H7g: Customers whose rate comparison shows a cumulative loss will change their behavior in subsequent months to minimize that loss.

The model to test this hypothesis will use the same data used to test hypothesis H7f, except that it will include an independent variable that equals unity if the customer has experienced a cumulative loss (i.e., where the sum of monthly CAP bills is higher than the sum of what those bills would have been under the flat rate), and zero otherwise. The hypothesis is that the coefficient on the variable that measures the cumulative loss will be positive, indicating a higher elasticity of substitution for customers who have experienced a cumulative loss.

H7h: Customers whose rate comparison shows a monthly gain will have a drop-out rate that is lower than customers who experience a monthly loss.

For purposes of testing this hypothesis and distinguishing it from H7i below, we interpret this hypothesis as follows: "Customers who drop out are more likely to have experienced a monthly loss in the previous month than a monthly gain in the previous month." This hypothesis is to be tested using the model developed to test hypothesis H2a (a logit model in which the dependent variable equals unity if the customer opted out of the pilot and zero if the customer did not). It will also be necessary to add an independent indicator variable that equals unity if the customer experienced a loss in the previous billing month, and zero otherwise. The hypothesis is that the coefficient on this variable will be positive.

H7i: Customers whose rate comparison shows a cumulative gain will have a drop-out rate that is lower than customers who experience a cumulative loss.

This hypothesis will also be tested using a logit model in which the dependent variable is unity for customers who have dropped out of the program and zero for those who have not. The analysis will omit customers who terminated service during the course of the pilot. The independent variables will represent the several rate and technology treatments, the education treatments, and an indicator variable that equals unity if the customer's aggregate CAP bill is less than the customer's aggregate bill on its standard residential rate. The hypothesis is that the coefficient on this variable will be negative, indicating that customers who have paid less on CAP than they would otherwise have paid were less likely to drop out of the program.

H7j: Customers who experience sequential monthly losses will have a drop-out rate that is higher than customers who do not experience sequential monthly losses.

This hypothesis will be tested using the same method used to test hypothesis H7h, but it will include an explanatory variable that equals unity for customers who have experienced sequential monthly losses in two or more consecutive months.

H7k: Customers receiving normative comparisons will experience greater energy efficiency, demand response, and load-shifting benefits than customers not receiving normative comparisons.

Because all customers who receive education also receive normative comparisons through OPOWER, this hypothesis cannot be distinguished from hypothesis H6a. Therefore, no separate test of this hypothesis will be conducted.

H7l: Customers whose normative comparisons show them having higher electricity consumption than their neighbors will lower their electricity consumption.

This hypothesis will be tested using the same model established elsewhere (such as for hypothesis H2b) to test for reductions in energy usage (conservation). We will add an indicator variable to this model that takes on a value of unity for customers whose OPOWER report indicates that they have higher electricity consumption than their neighbors, and zero otherwise.[53] The null hypothesis is that the coefficient on this variable will be negative.

[53] This information is not currently in the database. EPRI will work with OPOWER to add the required information to the database.

Customer Experience – Notifications

Except for customers in control applications F1 and F3, all CAP customers are notified of events by automated phone call (unless they choose to opt-out[54]); they may also choose to receive notification by email or text message. In addition, customers on the CPP, PTR, and DA-RTP rates are notified of high prices whenever an hourly price exceeds $0.13 per kWh.

H7m: Customers who are notified of events will experience greater energy efficiency, demand response, and load-shifting benefits than customers who are not notified.

As in some previous hypotheses, this is really a joint hypothesis, but each piece of it is tested separately. Thus, four separate regression models are specified, one for which the dependent variable is one of the four measures of electricity consumption focused on throughout this analysis. Furthermore, the model must include an independent variable that indicates the share of events for which a customer was successfully notified.[55] The hypothesis is that the coefficient on this variable will be negative in each model.

Table D-20 presents results for energy efficiency and demand response. The constant coefficients represent average hourly kWh usage for the customer group whose customers face the flat rate, have SFNS housing, basic education, and eWeb. The coefficients on the notification variable indicate the impact of notification on usage. For all three time periods, the high t-statistics on the coefficients for notification variable imply that notification is a significant determinant (at the 0.0% confidence level) of usage. Unfortunately, the positive signs on the coefficient indicate that notification increases (rather than reduces) usage.

Table D-20
Impact of Notification on Usage[56]

	All Periods			Peak Periods			Event Peaks		
Variable	**Coef.**	**S.E**	**t**	**Coef.**	**S.E**	**t**	**Coef.**	**S.E**	**t**
Constant	**1.502**	0.053	28.19	**1.726**	0.067	25.75	**2.389**	0.099	24.18
CPP	0.008	0.039	0.20	0.040	0.046	0.88	-0.030	0.062	-0.49
DA-RTP	0.050	0.043	1.16	**0.115**	0.052	2.21	0.104	0.070	1.49
PTR	0.012	0.043	0.27	0.048	0.051	0.94	0.017	0.068	0.24
TOU	0.054	0.043	1.26	0.066	0.051	1.29	0.053	0.069	0.76
BIHD	-0.020	0.027	-0.73	-0.019	0.035	-0.54	-0.014	0.046	-0.29

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[54] The early experience has been that about 20% of customers opt-out of phone notification.

[55] For example, because there were six events between June and August, the notification variable equals 0 if the customer was never successfully notified, 1/6 if the customer was successfully notified once, 2/6 if the customer was successfully notified of two events, and so on.

[56] All three regressions are based upon 5,262 observations and have R-squared values of approximately 0.20.

	All Periods			Peak Periods			Event Peaks		
Variable	**Coef.**	**S.E**	**t**	**Coef.**	**S.E**	**t**	**Coef.**	**S.E**	**t**
AIHD	0.029	0.032	0.92	0.039	0.039	0.99	0.067	0.052	1.29
PCT	0.013	0.039	0.33	-0.018	0.047	-0.38	-0.019	0.063	-0.31
Bill Protection	0.024	0.048	0.49	0.043	0.063	0.69	0.065	0.083	0.79
Purchase Tech.	-0.059	0.048	-1.22	-0.056	0.062	-0.90	-0.085	0.080	-1.06
Notification	**0.141**	0.025	5.59	**0.177**	0.032	5.61	**0.250**	0.042	5.92
Full Education	**-0.165**	0.067	-2.48	**-0.229**	0.083	-2.78	**-0.395**	0.118	-3.35
SFSH	0.044	0.193	0.23	0.117	0.254	0.46	-0.101	0.309	-0.33
MFNS	**-0.742**	0.019	-39.83	**-0.966**	0.023	-41.63	**-1.313**	0.031	-42.34
MFSH	**-0.688**	0.080	-8.66	**-0.925**	0.054	-17.07	**-1.278**	0.072	-17.85
Dependent variables: "All Periods" refers to average hourly kW usage for all days from June through August 2010, "Peak Periods" refers to average hourly kW usage during peak hours on non-holiday weekdays from June through August 2010, and "Event Peaks" refers to average hourly kW usage during peak hours on event days.									

Table D-21 presents the load-shifting results. The constant term shows the average ratio of peak to off-peak usage for the customer groups with a flat rate, eWeb, basic education, and SFNS housing. The t-statistic on the notification variable implies that notification is not a significant determinant of average ratios of peak to off-peak usage. In summary, the evidence does not support hypothesis H7m. [57]

Table D-21
Impact of Notification on Peak to Off-Peak Usage Ratios [58]

Variable	Coef.	S.E	t
Constant	**1.159**	0.024	47.90
CPP	0.006	0.017	0.39
DA-RTP	**0.042**	0.018	2.29
PTR	0.013	0.018	0.74
TOU	-0.011	0.018	-0.63
BIHD	0.002	0.012	0.14
AIHD	0.011	0.014	0.80
PCT	-0.012	0.017	-0.72

[57] Similar results were found by alternate specifications that either: a) added an interaction variable between notification and CPP; or b) excluded technology and purchase variables.
[58] The regression is based upon 5,262 observations, and has an R-squared of 0.07.

Variable	Coef.	S.E	t
Bill Protection	0.034	0.022	1.59
Purchase Tech.	0.003	0.020	0.17
Notification	0.018	0.012	1.55
Full Education	-0.018	0.030	-0.60
SFSH	0.074	0.074	1.00
MFNS	**-0.176**	0.009	-19.30
MFSH	**-0.104**	0.032	-3.27
Dependent variable: average hourly kW usage during peak hours divided by average hourly kW usage during off-peak hours for non-holiday weekdays from June through August 2010.			

H7n: Customers who choose more than one notification media will experience greater energy efficiency, demand response, and load-shifting benefits than customers who do not.

This hypothesis test includes the notification variable from hypothesis H7m, plus another indicator variable that equals unity for customers who have elected to receive notification through multiple media and zero otherwise. The null hypothesis is that the coefficient on this latter variable will be negative in each model.

Table D-22 presents results for energy efficiency and demand response. The constant coefficients represent average hourly kWh usage for the customer groups with a flat rate, eWeb, basic education, and SFNS housing. The coefficients on the dummy variables for Methods indicate the impact of multiple notification methods on usage. In all cases, the small t-statistics on the coefficients for the Methods variable implies that multiple notification methods is a not a significant determinant of usage in these periods.

Table D-22
Impact of Multiple Notification Methods on Usage[59]

	All Periods			Peak Periods			Event Peaks		
Variable	**Coef.**	**S.E**	**t**	**Coef.**	**S.E**	**t**	**Coef.**	**S.E**	**t**
Constant	**1.502**	0.053	28.19	**1.726**	0.067	25.75	**2.389**	0.099	24.18
CPP	0.008	0.040	0.20	0.040	0.046	0.88	-0.029	0.062	-0.47
DA-RTP	0.050	0.043	1.16	**0.115**	0.052	2.21	0.104	0.070	1.50
PTR	0.012	0.043	0.27	0.048	0.051	0.94	0.017	0.069	0.24
TOU	0.054	0.043	1.25	0.066	0.051	1.29	0.053	0.069	0.77
BIHD	-0.020	0.027	-0.73	-0.019	0.035	-0.54	-0.013	0.046	-0.29
AIHD	0.029	0.032	0.92	0.039	0.039	0.99	0.066	0.052	1.27
PCT	0.013	0.039	0.33	-0.018	0.047	-0.38	-0.020	0.063	-0.32
Bill Protection	0.024	0.048	0.49	0.043	0.063	0.69	0.065	0.083	0.78
Purchase Tech.	-0.059	0.048	-1.21	-0.056	0.062	-0.91	-0.087	0.080	-1.08
Notification	**0.141**	0.026	5.38	**0.178**	0.032	5.47	**0.254**	0.043	5.87
Methods	0.002	0.026	0.06	-0.004	0.033	-0.11	-0.021	0.044	-0.47
Full Education	**-0.166**	0.067	-2.48	**-0.229**	0.083	-2.78	**-0.394**	0.118	-3.35
SFSH	0.044	0.193	0.23	0.117	0.254	0.46	-0.101	0.309	-0.33
MFNS	**-0.742**	0.019	-39.83	**-0.966**	0.023	-41.62	**-1.313**	0.031	-42.34
MFSH	**-0.688**	0.080	-8.65	**-0.925**	0.054	-17.06	**-1.277**	0.072	-17.82

Dependent variables: "All Periods" refers to average hourly kW usage for all days from June through August 2010, "Peak Periods" refers to average hourly kW usage during peak hours on non-holiday weekdays from June through August 2010, and "Event Peaks" refers to average hourly kW usage during peak hours on event days.

Table D-23 presents the load-shifting results. The constant term shows the average peak to off-peak usage ratio for the customer groups with a flat rate, eWeb, basic education, and SFNS housing. The t-statistic on the Methods dummy implies that multiple notification methods are not a significant determinant of peak to off-peak usage ratios.

In summary, the evidence does not support hypothesis H7n.

[59] All three regressions are based upon 5,262 observations and have R-squared values of approximately 0.20.

Table D-23
Impact of Multiple Notification Methods on Peak to Off-Peak Usage Ratios [60]

Variable	Coef.	S.E	t
Constant	**1.159**	0.024	47.90
CPP	0.007	0.017	0.40
DA-RTP	**0.042**	0.018	2.29
PTR	0.013	0.018	0.74
TOU	-0.011	0.018	-0.62
BIHD	0.002	0.012	0.15
AIHD	0.011	0.014	0.79
PCT	-0.013	0.017	-0.72
Bill Protection	0.034	0.022	1.58
Purchase Tech.	0.003	0.020	0.16
Notification	0.019	0.012	1.60
Methods	-0.005	0.011	-0.45
Full Education	-0.018	0.031	-0.59
SFSH	0.074	0.074	1.00
MFNS	**-0.176**	0.009	-19.31
MFSH	**-0.104**	0.032	-3.26
Dependent variable: average hourly kW usage during peak hours divided by average hourly kW usage during off-peak hours for non-holiday weekdays from June through August 2010.			

H7o: Customers who view hourly pricing information online will experience greater energy efficiency, demand response, and load-shifting benefits than customers who do not.

When the needed survey information becomes available, this test will build upon the test of hypothesis H7m by including an indicator variable for customers who have viewed hourly pricing information.[61] We may also construct interaction variables between this variable and the indicator variables for rate treatment RTP, CPP, and PTR (which charge hourly prices) if any

[60] The regression is based upon 5,262 observations, and has an R-squared of 0.07.

[61] EPRI is exploring whether we will know that customers viewed hourly pricing information, such as on the OPOWER web site. However, EPRI will probably *not* be able to ascertain whether or not the customers viewed prices on their BIHD or AIHD. If the currently available data are found to be inadequate, EPRI may add a survey question regarding the customer's price-viewing behavior.

non-hourly customers view hourly prices. The interaction would indicate whether viewing the hourly prices has a larger effect when customers are charged those prices. The hypothesis is that the coefficient on the price-viewing variables will be negative in each model. The results from the three models will be summarized using the same method described in the test of hypothesis H2e. If appropriate, the multivariate ANOVA model will be employed here.

H7p: Customers who sign up one or more family members for notification will experience greater energy efficiency, demand response, and load-shifting benefits than customers who do not.

This test builds upon the test of hypothesis H7m by including an indicator variable for customers who signed up more than one family member to receive event and high price notifications.[62] The hypothesis is that the coefficient on this variable will be negative in each model. The results from the three models will be summarized using the same method described in the test of hypothesis H2e. If appropriate, the multivariate ANOVA model will be employed here.

Customer Experience – Customer Support

The final set of hypotheses relate to the nature and/or effect of CAP customers' experience in contacting the customer support center. The CAP customer support center is staffed by specially-trained individuals who provide telephone and email support. ComEd has outsourced this function.

H7q: Customers who contact the customer support center will experience greater energy efficiency, demand response, and load-shifting benefits than customers who do not.

This test is similar to the test of hypothesis H7n, but replaces the event notification variables with an indicator variable that equals unity if the customer ever contacted the CAP customer support center and zero if it did not. The hypothesis is that the coefficient on the customer contact variable is negative in each model.

Table D-24 presents results for energy efficiency and demand response. The coefficients on the dummy variable for Contact indicate the impact on usage of a customer making any contact with the utility. None of the coefficients for the "Contact" variable is statistically significant. Although the "Contact" coefficient is quite close to being statistically significant in the "All Periods" model, its sign is positive, contradicting the hypothesis.

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[62] This information may need to be obtained from the 2011 survey.

Table D-24
Impact of Customer Contacts on Usage[63]

	All Periods			Peak Periods			Event Peaks		
Variable	**Coef.**	**S.E**	**t**	**Coef.**	**S.E**	**t**	**Coef.**	**S.E**	**t**
Constant	**1.501**	0.053	28.16	**1.726**	0.067	25.73	**2.388**	0.099	24.15
CPP	0.006	0.040	0.16	0.040	0.046	0.87	-0.031	0.063	-0.49
DA-RTP	0.047	0.043	1.10	**0.113**	0.052	2.17	0.101	0.070	1.45
PTR	0.009	0.043	0.20	0.045	0.051	0.88	0.013	0.069	0.18
TOU	0.048	0.043	1.12	0.061	0.051	1.19	0.046	0.070	0.66
BIHD	-0.034	0.029	-1.18	-0.028	0.037	-0.76	-0.028	0.048	-0.58
AIHD	0.024	0.032	0.76	0.037	0.040	0.94	0.064	0.053	1.21
PCT	0.004	0.040	0.11	-0.024	0.047	-0.51	-0.029	0.063	-0.46
Bill Protection	0.027	0.048	0.57	0.049	0.063	0.78	0.073	0.083	0.87
Purchase Tech.	-0.044	0.049	-0.89	-0.044	0.063	-0.70	-0.067	0.081	-0.82
Contact	0.051	0.026	1.95	0.038	0.033	1.15	0.059	0.045	1.32
Full Education	-0.060	0.065	-0.92	-0.097	0.080	-1.22	-0.208	0.114	-1.82
SFSH	0.062	0.194	0.32	0.141	0.256	0.55	-0.068	0.311	-0.22
MFNS	**-0.741**	0.019	-39.41	**-0.967**	0.023	-41.26	**-1.314**	0.031	-41.98
MFSH	**-0.698**	0.080	-8.75	**-0.936**	0.055	-17.16	**-1.294**	0.072	-18.02
Dependent variables: "All Periods" refers to average hourly kW usage for all days from June through August 2010, "Peak Periods" refers to average hourly kW usage during peak hours on non-holiday weekdays from June through August 2010, and "Event Peaks" refers to average hourly kW usage during peak hours on event days.									

Table D-25 presents the load-shifting results. The small t-statistic on the coefficient on the Contact dummy variable also suggests that customer contacts do not significantly affect peak to off-peak usage ratios.

[63] All three regressions are based upon 5,262 observations and the R-squared value is approximately 0.20.

Table D-25
Impact of Customer Contacts on Peak to Off-Peak Usage Ratios [64]

Variable	Coef.	S.E	t
Constant	**1.160**	0.024	47.94
CPP	0.008	0.017	0.46
DA-RTP	**0.042**	0.018	2.32
PTR	0.014	0.018	0.76
TOU	-0.010	0.018	-0.58
BIHD	0.006	0.013	0.46
AIHD	0.013	0.014	0.96
PCT	-0.010	0.017	-0.60
Bill Protection	0.035	0.022	1.62
Purchase Tech.	0.001	0.020	0.04
Contact	-0.011	0.011	-0.98
Full Education	-0.005	0.029	-0.17
SFSH	0.077	0.073	1.05
MFNS	**-0.177**	0.009	-19.28
MFSH	**-0.105**	0.032	-3.30
Dependent variable: average hourly kW usage during peak hours divided by average hourly kW usage during off-peak hours for non-holiday weekdays from June through August 2010.			

In summary, the evidence from these three models does not support hypothesis H7q.

H7r: Customers on the CPP rate will contact the customer support center more frequently than customers on other rates.

This hypothesis is tested using a Poisson regression model, which is appropriate when the dependent variable is a count variable.[65] The dependent variable is the number of times the

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[64] The regression is based upon 5,262 observations, and has an R-squared of 0.07.

[65] According to Greene (*Econometric Analysis*. 5th edition, Englewood Cliffs, NJ: Prentice Hall, Inc., 2003, Chapter 21), one could use ordinary linear regression to conduct the analysis when the dependent variable consists of count data, but because of the number of zeros, the small values and the discrete nature of the data, one can improve on the results by specification of a model that accounts for these characteristics of the dependent variable. The Poisson model is widely used for this purpose. The Poisson regression model specifies that each of the dependent variables is drawn from a Poisson distribution rather than a normal distribution.

customer has contacted the customer support center. The independent variables represent the rate and technology treatments. Because dummy variables are specified to represent all rate treatments, except for CPP which is the control group, the hypothesis is that the coefficients on the dummy variables for the rate treatments will all be negative, indicating that customers on the other rates have contacted the customer support center less frequently than have CPP customers.

Table D-26 presents the results. The constant coefficient is the natural log of 1.27, which is the average number of contacts by CPP customers with eWeb and SFNS housing. The other coefficients indicate how customers in the indicated rate treatments and using the indicated technologies differ from CPP customers with eWeb and SFNS housing. The small z-statistics for the coefficients on the dummy variables for all other rate treatments indicate that rate treatments do not significantly affect the number of contacts. Thus, the evidence does not support the hypothesis.

As might be expected, the coefficients for the technology treatment indicators (BIHD, AIHD, and PCT) are all positive and statistically significant, which reflects the fact that customers with those technologies must (in some cases) call customer support to activate the device and are probably more likely to need technical support.

Table D-26
Impact of Rate and Technology on Number of Customer Contacts[66]

Variable	Coef.	S.E	z
Constant	0.241	0.418	0.58
Flat Rate	-0.042	0.087	-0.49
DA-RTP	-0.047	0.074	-0.63
IBR	-0.104	0.082	-1.27
PTR	0.026	0.067	0.39
TOU	0.070	0.066	1.05
BIHD	**0.231**	0.111	2.08
AIHD	**0.512**	0.115	4.46
PCT	**0.539**	0.124	4.35
Bill Protection	-0.007	0.211	-0.03
Purchase Tech.	-0.061	0.140	-0.43
Full Education	-0.009	0.428	-0.02
SFSH	0.164	0.318	0.52
MFNS	-0.086	0.049	-1.76

[66] The regression is based upon 1,329 observations, and has a pseudo-R-squared of 0.02.

Variable	Coef.	S.E	z
MFSH	0.178	0.129	1.38
Dependent variable: count variable that equals the number of times the customer contacted the customer support center.			

H7s: Customers on the CPP rate will have call durations that are longer than the durations for customers on other rates.

This hypothesis is tested using a regression model in which the dependent variable is the call duration and the independent variables represent the rate and technology treatments types and an indicator for an event day (or the day prior to an event day, when the customer is notified). Because dummy variables are specified to represent all rate treatments except for CPP, the hypothesis is that the coefficients on the dummy variables for the rate treatments will be negative, indicating that customers in the other rate treatments have contacted the customer support center for shorter durations than did CPP customers.

Table D-27 presents results in which the constant coefficient represents the average call duration (in seconds) by CPP customers with eWeb and SFNS housing. The other coefficients indicate how customers' average call durations in the indicated rate treatments and using the indicated technologies differ from those for CPP customers with eWeb and SFNS housing. The small t-statistics on the coefficients for all the dummy variables representing the rate treatments indicate that rate treatments do not significantly affect the duration of contacts. Thus, the evidence does not support the hypothesis.[67]

Table D-27
Impact of Rate and Technology on Call Duration[68]

Variable	Coef.	S.E	t
Constant	**176.166**	28.875	6.10
Flat Rate	-7.766	26.525	-0.29
DA-RTP	-24.678	18.875	-1.31
IBR	-33.325	21.254	-1.57
PTR	-10.314	21.131	-0.49
TOU	-21.127	18.668	-1.13
BIHD	13.871	39.661	0.35

[67] Several alternate specifications yielded similar results. The alternate specifications were: a) addition of interaction dummies between rate type and events; b) addition of interaction dummies between rate type and events accompanied by deletion of the event dummy; c) deletion of the event dummy; and d) deletion of the event dummy and IBR.
[68] The regression is based upon 1,968 observations, and has an R-squared of 0.01.

Variable	Coef.	S.E	t
AIHD	-16.713	41.197	-0.41
PCT	-11.477	45.466	-0.25
Bill Protection	-90.100	52.856	-1.70
Purchase Tech.	**-78.755**	30.932	-2.55
Full Education	**160.321**	45.929	3.49
SFSH	90.314	85.062	1.06
MFNS	-2.267	13.927	-0.16
MFSH	36.304	33.790	1.07
Event	-32.948	33.147	-0.99
Dependent variable: variable indicating the length of calls placed to the customer support center in seconds.			

H7t: Customers who are eligible to receive the BIHD will contact the customer support center more frequently than customers eligible to receive other enabling technology.

The model used to test hypothesis H7r is similar to the one used to test this hypothesis except that, to measure contacts relative to BIHD, the regression was re-ordered so that the constant coefficient represents the number of contacts by flat rate customers with BIHD and SFNS housing. Consequently, the hypothesis is that the coefficients on the technology variables are negative. In keeping with the wording of the hypothesis, the technology variables include all customers in the treatment cells rather than only those who implemented and/or adopted the technology.

In Table D-28 the large z-statistics for all three technology variables suggests that the number of calls varies significantly by technology. Customers with eWeb call less frequently than customers with BIHD, with the difference being significant at the 5% level. Customers with AIHD and PCT call more frequently than customers with BIHD, with the differences being significant at the 0.0% level. For this reason, hypothesis H7t is not supported by the evidence. Rather the opposite appears to be true: the number of calls increases with the complexity of the technology.

Table D-28
Impact of Rate and Technology on Number of Customer Contacts [69]

Variable	Coef.	S.E	z
Constant	0.430	0.423	1.02
CPP	0.042	0.087	0.49
DA-RTP	-0.005	0.095	-0.05
IBR	-0.062	0.101	-0.62
PTR	0.068	0.092	0.74
TOU	0.112	0.088	1.26
eWeb	**-0.231**	0.111	-2.08
AIHD	**0.281**	0.053	5.34
PCT	**0.308**	0.073	4.19
Bill Protection	-0.007	0.211	-0.03
Purchase Tech.	-0.061	0.140	-0.43
Full Education	-0.009	0.428	-0.02
SFSH	0.164	0.318	0.52
MFNS	-0.086	0.049	-1.76
MFSH	0.178	0.129	1.38
Dependent variable: count variable that equals the number of times the customer contacted the customer support center.			

H7u: Customers who are eligible to receive the BIHD will have call durations that are longer than durations for customers eligible to receive other enabling technology.

The model used to test hypothesis H7s is also be used to test this model except that, to measure call durations relative to BIHD, the regression was re-ordered so that the constant coefficient represents call durations by flat rate customers with BIHD and SFNS housing. Consequently, the hypothesis is that the coefficients on the technology variables are negative. In keeping with the wording of the hypothesis, the technology variables include all customers in the treatment cells rather than only those who implemented and/or adopted the technology.

The results in Table D-29 contain a high t-statistic for the coefficient associated with the AIHD variable, which indicates that call duration is significantly shorter (at the 5% level of significance) for AIHD customers compared with customers with BIHD. This is consistent with

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[69] The regression is based upon 1,329 observations, and has an R-squared of 0.02.

the hypothesis, though the finding for PCT is not. Thus, the evidence provides some support for hypothesis H7u.[70]

Table D-29
Impact of Rate and Technology on Call Duration[71]

Variable	Coef.	S.E	t
Constant	**182.271**	41.270	4.42
CPP	7.766	26.525	0.29
DA-RTP	-16.912	26.960	-0.63
IBR	-25.559	28.439	-0.90
PTR	-2.548	29.066	-0.09
TOU	-13.361	26.472	-0.50
eWeb	-13.871	39.661	-0.35
AIHD	**-30.585**	15.152	-2.02
PCT	-25.348	23.843	-1.06
Bill Protection	-90.100	52.856	-1.70
Purchase Tech.	**-78.755**	30.932	-2.55
Full Education	**160.321**	45.929	3.49
SFSH	90.314	85.062	1.06
MFNS	-2.267	13.927	-0.16
MFSH	36.304	33.790	1.07
Event	-32.948	33.147	-0.99
Dependent variable: variable indicating the length of calls placed to the customer support center in seconds.			

H7v: Customer satisfaction with customer support center will exceed satisfaction levels of ComEd's customer care center.

As indicated numerous times above, the test of this hypothesis must rely on information about customer satisfaction with the CAP customer support center. These data are to be collected as part of the exit survey. In conducting the tests, it may also be useful to compare data on customer satisfaction from the exit survey with data provided by ComEd from recent customer satisfaction surveys regarding the general ComEd customer support center. The results will be available in the Phase 2 report.

---

[70] Several alternate specifications yielded similar results. The alternate specifications were essentially identical to those of hypothesis H7s.
[71] The regression is based upon 1,968 observations, and has an R-squared of 0.01.

E
TECHNICAL SUMMARIES

The variable labels defined below frequently appear in the Stata output tables and/or are referenced in the summaries:

Dependent Variables

- `usage` Average hourly kW usage for all days from June through August 2010
- `peak` Average hourly kW usage during peak hours (1:00pm to 5:00pm) on non-holiday weekdays from June through August 2010
- `event_peak` Average hourly kW usage during peak hours (1:00pm to 5:00pm) on event days
- `peak_offpeak` Average peak hourly usage divided by average off-peak hourly usage on non-holiday weekdays from June through August 2010
- `ln_avg_usage` Natural log of kW usage during a specific billing month averaged across customers in the IBR treatment cells
- `optout` Binary choice variable that equals one if the customer opted out of the pilot program and zero otherwise
- `implement` Binary choice variable that equals one if the customer implemented the technology and zero otherwise
- `contacts` Count variable that equals the number of times the customer has contacted the customer support center
- `callduration` Variable indicating the length of calls placed to the customer support center in seconds

Independent Variables

- Rate type indicators equal one if the customer is subject to a particular rate structure and equal zero otherwise.
  - `cpp` corresponds to the critical peak pricing rate structure
  - `dap` corresponds to the day-ahead real-time pricing rate structure
  - `flr` corresponds to the flat rate structure
  - `ibr` corresponds to the inclining block rate structure
  - `ptr` corresponds to the peak-time rebate rate structure
  - `tou` corresponds to the time-of-use pricing rate structure
- Technology type indicators equal one if the customer is in a treatment cell that offers a particular technology and equal zero otherwise.
  - `bihd` corresponds to the Basic In-Home Display (BIHD) treatment cells
  - `aihd` corresponds to the Advanced In-Home Display (AIHD) treatment cells

- `pct` corresponds to the Advanced In-Home Display plus Programmable Communicating Thermostat (AIHD/PCT) treatment cells
- `eweb` corresponds to the Enhanced Web (eWeb) treatment cells

- Technology implementation indicators that are interactions between the technology variables and whether the customer implemented (i.e., installed) the technology. These variables equal one if the customer is in a treatment cell offering a particular technology *and* the customer implemented (i.e. installed) the technology and equal zero otherwise.
  - `bihd_imp` corresponds to customers in a BIHD treatment cell who have installed their device
  - `aihd_imp` corresponds to customers in an AIHD treatment cell who have installed their device
  - `pct_imp` corresponds to customers in an AIHD/PCT treatment cell who have installed their device

- Housing type indicators equal one if the customer resides in a particular class of residential housing and equal zero otherwise.
  - `SFNS` corresponds to customers in single-family residences with non-space heating
  - `SFSH` corresponds to customers in single-family residences with space heating
  - `MFNS` corresponds to customers in multi-family residences with non-space heating
  - `MFSH` corresponds to customers in multi-family residences with space heating

- Cell type indicators equal one if the customer is in a particular treatment cell and equal zero otherwise.
  - `d1` corresponds to customers in treatment cell D1a
  - `l1` corresponds to customers in treatment cell L1a
  - `l5` corresponds to customers in treatment cell L5a
  - `l6` corresponds to customers in treatment cell L6a
  - `f6_or_f7` corresponds to customers in treatment cells F6 or F7
  - All other variable labels match the treatment cells as outlined in the report.

- Other treatment conditions are identified using indicators that equal one when the customer satisfies the particular condition and equal zero otherwise.
  - `bill_prot` corresponds to customers who were notified of bill protection
  - `purch_tech` corresponds to customers who were offered the opportunity to purchase enabling technology
  - `full_educ` corresponds to customers who received education beyond the basic education offered to customers in cell F3
  - `notify_share` corresponds to the share of events for which a customer was successfully notified (i.e. can equal either 0, 1/6, 2/6, etc.)
  - `methods` corresponds to customers who have elected to receive notification through multiple media

- o anycontact corresponds to customers who ever contacted the CAP customer support center
- o event corresponds to event days in models where the observations are date-specific

- _cons represents the constant in the regression equation.

Report Tables

Table 5-1 Estimated Coefficients from the ANOVA Models

Table 5-1 contains results from the four models detailed below. Each model contains one observation per customer; and customers are excluded if they are in treatment cells F1 or F2, are in any of the IBR treatment cells, or are screened due to data problems discussed in the report. The control group consists of customers in treatment cell F3 residing in single-family homes with non-space heating.

- Linear regression model using robust standard errors where the dependent variable is usage.

```
                                                       Number of obs =    5262
                                                       F( 13,  5248) =  124.34
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.1936
                                                       Root MSE      =  .73794

------------------------------------------------------------------------------
             |               Robust
       usage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         cpp |   .0105061   .0396595     0.26   0.791     -.067243    .0882552
         dap |   .0500449   .0431413     1.16   0.246      -.03453    .1346197
         ptr |   .0107828   .0428695     0.25   0.801    -.0732592    .0948248
         tou |   .0532086   .0432238     1.23   0.218    -.0315281    .1379453
        bihd |  -.0167791   .0273173    -0.61   0.539    -.0703325    .0367742
        aihd |   .0326648   .0315776     1.03   0.301    -.0292404      .09457
         pct |   .0133519   .0392238     0.34   0.734    -.0635431    .0902469
   bill_prot |   .0281828   .0481903     0.58   0.559    -.0662903    .1226559
  purch_tech |  -.0570161    .048354    -1.18   0.238    -.1518101    .0377778
   full_educ |  -.0609152   .0648714    -0.94   0.348    -.1880902    .0662597
        SFSH |   .0641051   .1948932     0.33   0.742    -.3179666    .4461768
        MFNS |  -.7438072   .0186541   -39.87   0.000    -.7803769   -.7072375
        MFSH |  -.6968371   .0797475    -8.74   0.000    -.8531754   -.5404987
       _cons |   1.503251   .0532852    28.21   0.000      1.39879    1.607712
------------------------------------------------------------------------------
```

- Linear regression model using robust standard errors where the dependent variable is peak.

```
                                                       Number of obs =    5262
                                                       F( 13,  5248) =  137.43
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.2056
                                                       Root MSE      =  .92855

------------------------------------------------------------------------------
             |               Robust
        peak |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         cpp |   .0435275   .0461808     0.94   0.346     -.047006     .134061
```

	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
dap	.1149525	.0521365	2.20	0.028	.0127432	.2171617
ptr	.0464339	.0509584	0.91	0.362	-.0534657	.1463336
tou	.0645381	.0511321	1.26	0.207	-.0357022	.1647783
bihd	-.0151454	.0349729	-0.43	0.665	-.0837068	.0534161
aihd	.0434226	.0391066	1.11	0.267	-.0332427	.1200879
pct	-.0171761	.047162	-0.36	0.716	-.1096332	.075281
bill_prot	.0492972	.0626946	0.79	0.432	-.0736102	.1722047
purch_tech	-.0538631	.0620194	-0.87	0.385	-.175447	.0677208
full_educ	-.0982762	.0799573	-1.23	0.219	-.2550258	.0584734
SFSH	.1420366	.2560194	0.55	0.579	-.3598679	.6439411
MFNS	-.9692645	.0232692	-41.65	0.000	-1.014882	-.9236472
MFSH	-.9352494	.0546189	-17.12	0.000	-1.042325	-.8281736
_cons	1.727603	.0670352	25.77	0.000	1.596186	1.85902

- Linear regression model using robust standard errors where the dependent variable is `event_peak`.

```
Number of obs =    5262
F( 13,  5248) =  141.95
Prob > F      =  0.0000
R-squared     =  0.2121
Root MSE      =  1.2411
```

event_peak	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
cpp	-.025466	.0623985	-0.41	0.683	-.1477932	.0968611
dap	.10446	.0699721	1.49	0.136	-.0327144	.2416344
ptr	.015013	.0688148	0.22	0.827	-.1198926	.1499186
tou	.0511518	.0694691	0.74	0.462	-.0850366	.1873401
bihd	-.0082411	.0461322	-0.18	0.858	-.0986793	.0821972
aihd	.0732734	.0520625	1.41	0.159	-.0287907	.1753375
pct	-.0187144	.0629698	-0.30	0.766	-.1421615	.1047327
bill_prot	.0736126	.0834287	0.88	0.378	-.0899424	.2371676
purch_tech	-.082295	.0803425	-1.02	0.306	-.2397998	.0752098
full_educ	-.2093572	.114258	-1.83	0.067	-.4333504	.014636
SFSH	-.0656791	.3114828	-0.21	0.833	-.676315	.5449568
MFNS	-1.317351	.031092	-42.37	0.000	-1.378304	-1.256398
MFSH	-1.292809	.0718369	-18.00	0.000	-1.433639	-1.151979
_cons	2.390548	.0987947	24.20	0.000	2.19687	2.584227

- Linear regression model using robust standard errors where the dependent variable is `peak_offpeak`.

```
Number of obs =    5262
F( 13,  5248) =   31.54
Prob > F      =  0.0000
R-squared     =  0.0686
Root MSE      =  .31928
```

peak_offpeak	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
cpp	.0067588	.0166028	0.41	0.684	-.0257897	.0393073
dap	.0415613	.018171	2.29	0.022	.0059387	.0771839
ptr	.013082	.0178093	0.73	0.463	-.0218316	.0479956
tou	-.0112384	.0175368	-0.64	0.522	-.0456178	.0231411
bihd	.0021658	.0123434	0.18	0.861	-.0220325	.026364

```
         aihd |   .0113001   .0135136     0.84   0.403    -.0151921    .0377923
          pct |  -.0123764   .0173329    -0.71   0.475    -.0463561    .0216034
    bill_prot |   .0350579   .0217039     1.62   0.106    -.0074909    .0776067
   purch_tech |   .0036473   .0199347     0.18   0.855    -.0354331    .0427277
    full_educ |   -.004837   .0294512    -0.16   0.870    -.0625737    .0528997
         SFSH |   .0767609   .0736564     1.04   0.297    -.0676363    .2211581
         MFNS |  -.1759992    .009092   -19.36   0.000    -.1938233   -.1581751
         MFSH |  -.1050703   .0318221    -3.30   0.001    -.1674549   -.0426856
        _cons |   1.159357    .024199    47.91   0.000     1.111917    1.206797
------------------------------------------------------------------------------
```

Table 5-3 Average Load Impacts of Responders, by Rate

The output tables below contain results of linear regression models estimated using data for customers identified as responders, aggregated by rate type. There is one observation per day. Table 5-3 in the report presents a summary of these results. The dependent variable is peak, as defined above. The variable labels in the output tables are defined as follows:

- `avg_peak_~65` Average peak-period cooling degree hours (using 65 degrees as the baseline value)
- `avg_prepe~65` Average cooling degree hours for the period prior to the peak-period (using 65 degrees as the baseline value)
- `thi` Temperature-Humidity Index = (0.55 * average temperature) + (0.2 * average dewpoint) + 17.5
- `thi_lag1` One day lagged value of the Temperature-Humidity Index
- `dt2` Indicator variable that equals one on Tuesday and zero otherwise
- `dt3` Indicator variable that equals one on Wednesday and zero otherwise
- `dt4` Indicator variable that equals one on Thursday and zero otherwise
- `dt5` Indicator variable that equals one on Friday and zero otherwise
- `m7` Indicator variable that equals one on days in July and zero otherwise
- `m8` Indicator variable that equals one on days in August and zero otherwise
- `event1` Indicator variable that equals one on the first event-day, July 14, 2010, and zero otherwise
- `event2` Indicator variable that equals one on the second event-day, July 23, 2010, and zero otherwise
- `event3` Indicator variable that equals one on the third event-day, July 27, 2010, and zero otherwise
- `event4` Indicator variable that equals one on the fourth event-day, August 19, 2010, and zero otherwise
- `event5` Indicator variable that equals one on the fifth event-day, August 20, 2010, and zero otherwise
- `event6` Indicator variable that equals one on the sixth event-day, August 31, 2010, and zero otherwise
- `_cons` constant

- **CPP responders**

Source	SS	df	MS
Model	7.58035663	16	.473772289
Residual	.572797995	49	.011689755
Total	8.15315462	65	.125433148

Number of obs	= 66
F(16, 49)	= 40.53
Prob > F	= 0.0000
R-squared	= 0.9297
Adj R-squared	= 0.9068
Root MSE	= .10812

peak	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
avg_peak_~65	.0235374	.0068095	3.46	0.001	.0098532	.0372216
avg_prepe~65	.0019158	.0080069	0.24	0.812	-.0141746	.0180062
thi	.0438598	.0120344	3.64	0.001	.0196757	.068044
thi_lag1	.0084414	.0056571	1.49	0.142	-.0029269	.0198097
dt2	.0277264	.0437698	0.63	0.529	-.0602323	.1156851
dt3	-.0151443	.0444485	-0.34	0.735	-.1044668	.0741782
dt4	-.0070593	.0442395	-0.16	0.874	-.095962	.0818434
dt5	.0764429	.0497129	1.54	0.131	-.0234589	.1763447
m7	.0554095	.0407614	1.36	0.180	-.0265036	.1373226
m8	-.1551116	.0375433	-4.13	0.000	-.2305576	-.0796655
event1	-.4807898	.1167279	-4.12	0.000	-.7153634	-.2462163
event2	-.464389	.1238853	-3.75	0.000	-.7133459	-.2154321
event3	-.6137059	.1186877	-5.17	0.000	-.8522177	-.375194
event4	-.457676	.1198235	-3.82	0.000	-.6984704	-.2168816
event5	-.7558	.117238	-6.45	0.000	-.9913986	-.5202014
event6	-.5737424	.1159211	-4.95	0.000	-.8066947	-.3407902
_cons	-2.811511	.8185236	-3.43	0.001	-4.456396	-1.166626

- **RTP responders**

Source	SS	df	MS
Model	10.6681972	16	.666762323
Residual	1.72845432	49	.035274578
Total	12.3966515	65	.190717715

Number of obs	= 66
F(16, 49)	= 18.90
Prob > F	= 0.0000
R-squared	= 0.8606
Adj R-squared	= 0.8150
Root MSE	= .18782

peak	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
avg_peak_~65	.0337276	.0118289	2.85	0.006	.0099566	.0574986
avg_prepe~65	-.005667	.0139088	-0.41	0.685	-.0336179	.0222838
thi	.0510839	.0209052	2.44	0.018	.0090733	.0930944
thi_lag1	.0120003	.009827	1.22	0.228	-.0077477	.0317483
dt2	.0395217	.0760331	0.52	0.606	-.1132725	.1923159
dt3	-.0622908	.077212	-0.81	0.424	-.2174541	.0928726
dt4	-.0547536	.0768491	-0.71	0.480	-.2091877	.0996804
dt5	-.0866699	.0863569	-1.00	0.320	-.2602107	.0868708
m7	.0172875	.0708072	0.24	0.808	-.1250049	.1595799
m8	-.0338334	.065217	-0.52	0.606	-.1648919	.097225
event1	.1661714	.2027696	0.82	0.416	-.2413095	.5736522
event2	.1826153	.2152029	0.85	0.400	-.2498511	.6150816
event3	-.2743393	.206174	-1.33	0.189	-.6886614	.1399829
event4	.2051604	.2081471	0.99	0.329	-.2131269	.6234477
event5	.2309501	.2036557	1.13	0.262	-.1783114	.6402117
event6	.1961647	.2013681	0.97	0.335	-.2084997	.6008291
_cons	-3.439457	1.421868	-2.42	0.019	-6.296808	-.582105

- **FLR responders**

```
      Source |       SS       df       MS              Number of obs =      66
-------------+------------------------------           F( 16,    49) =   28.01
       Model |  7.2768189    16  .454801181           Prob > F      =  0.0000
    Residual |  .795500666    49  .016234707           R-squared     =  0.9015
-------------+------------------------------           Adj R-squared =  0.8693
       Total |  8.07231956    65  .124189532           Root MSE      =  .12742

------------------------------------------------------------------------------
        peak |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
avg_peak_~65 |   .0337527   .0080248     4.21   0.000     .0176262    .0498792
avg_prepe~65 |   .0263912   .0094359     2.80   0.007     .0074291    .0453533
         thi |   .0141569   .0141823     1.00   0.323    -.0143434    .0426573
    thi_lag1 |   .0044792   .0066667     0.67   0.505     -.008918    .0178765
         dt2 |   .0290242   .0515815     0.56   0.576    -.0746327    .1326811
         dt3 |  -.0483842   .0523813    -0.92   0.360    -.1536483    .0568799
         dt4 |  -.0245057   .0521351    -0.47   0.640    -.1292751    .0802637
         dt5 |   .0166912   .0585853     0.28   0.777    -.1010404    .1344227
          m7 |   -.022215   .0480362    -0.46   0.646    -.1187474    .0743174
          m8 |  -.1091377   .0442438    -2.47   0.017    -.1980488   -.0202265
      event1 |  -.3424187   .1375607    -2.49   0.016    -.6188572   -.0659802
      event2 |  -.4037732   .1459955    -2.77   0.008    -.6971621   -.1103844
      event3 |  -.5730807   .1398702    -4.10   0.000    -.8541604   -.2920011
      event4 |  -.0629317   .1412088    -0.45   0.658    -.3467014     .220838
      event5 |  -.3261904   .1381618    -2.36   0.022    -.6038369   -.0485439
      event6 |   -.375361   .1366099    -2.75   0.008    -.6498888   -.1008331
       _cons |   -.840614   .9646078    -0.87   0.388    -2.779066    1.097838
------------------------------------------------------------------------------
```

- **IBR responders**

```
      Source |       SS       df       MS              Number of obs =      66
-------------+------------------------------           F( 16,    49) =   12.21
       Model |  6.27160644    16  .391975403           Prob > F      =  0.0000
    Residual |  1.57254984    49  .032092854           R-squared     =  0.7995
-------------+------------------------------           Adj R-squared =  0.7341
       Total |  7.84415629    65  .120679327           Root MSE      =  .17914

------------------------------------------------------------------------------
        peak |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
avg_peak_~65 |    .030811   .0112828     2.73   0.009     .0081374    .0534846
avg_prepe~65 |   .0077887   .0132667     0.59   0.560    -.0188719    .0344492
         thi |   .0282374   .0199401     1.42   0.163    -.0118337    .0683086
    thi_lag1 |  -.0011163   .0093733    -0.12   0.906    -.0199527    .0177201
         dt2 |   .0493847    .072523     0.68   0.499    -.0963557    .1951252
         dt3 |  -.0430409   .0736475    -0.58   0.562    -.1910411    .1049594
         dt4 |  -.0190454   .0733014    -0.26   0.796      -.16635    .1282592
         dt5 |  -.0673766   .0823703    -0.82   0.417    -.2329059    .0981527
          m7 |    .049982   .0675384     0.74   0.463    -.0857415    .1857054
          m8 |  -.0418184   .0622062    -0.67   0.505    -.1668265    .0831897
      event1 |  -.0277742   .1934088    -0.14   0.886    -.4164437    .3608952
      event2 |   .3558983    .205268     1.73   0.089    -.0566032    .7683999
      event3 |  -.6516922    .196656    -3.31   0.002    -1.046887   -.2564972
      event4 |  -.2995967    .198538    -1.51   0.138    -.6985738    .0993803
      event5 |  -.0401909    .194254    -0.21   0.837    -.4305589    .3501771
      event6 |  -.5108549    .192072    -2.66   0.011     -.896838   -.1248718
       _cons |  -1.265514   1.356228    -0.93   0.355    -3.990956    1.459928
------------------------------------------------------------------------------
```

- **PTR responders**

```
      Source |       SS       df       MS              Number of obs =      66
-------------+------------------------------           F( 16,    49) =   26.10
       Model |  4.36273347    16  .272670842           Prob > F      =  0.0000
    Residual |  .511959452    49  .010448152           R-squared     =  0.8950
-------------+------------------------------           Adj R-squared =  0.8607
       Total |  4.87469292    65  .074995276           Root MSE      =  .10222

------------------------------------------------------------------------------
        peak |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
avg_peak_~65 |    .022666   .0064377     3.52   0.001     .0097289    .0356031
avg_prepe~65 |  -.0026785   .0075697    -0.35   0.725    -.0178904    .0125334
         thi |   .0304646   .0113774     2.68   0.010     .0076008    .0533283
    thi_lag1 |   .0113143   .0053482     2.12   0.039     .0005666    .0220619
         dt2 |   .0125534   .0413801     0.30   0.763     -.070603    .0957098
         dt3 |  -.0407844   .0420217    -0.97   0.337    -.1252302    .0436614
         dt4 |  -.0260896   .0418242    -0.62   0.536    -.1101384    .0579593
         dt5 |   .0619577   .0469987     1.32   0.194    -.0324898    .1564052
          m7 |  -.0134959    .038536    -0.35   0.728    -.0909368    .0639451
          m8 |  -.1536908   .0354936    -4.33   0.000    -.2250178   -.0823639
      event1 |  -.2553453   .1103549    -2.31   0.025    -.4771119   -.0335788
      event2 |  -.3228305   .1171216    -2.76   0.008    -.5581951   -.0874659
      event3 |  -.3893662   .1122077    -3.47   0.001     -.614856   -.1638764
      event4 |  -.3790791   .1132816    -3.35   0.002    -.6067269   -.1514313
      event5 |  -.5794412   .1108372    -5.23   0.000    -.8021768   -.3567055
      event6 |  -.3444482   .1095922    -3.14   0.003    -.5646819   -.1242145
       _cons |   -2.22329   .7738348    -2.87   0.006    -3.778369   -.6682104
------------------------------------------------------------------------------
```

- **TOU responders**

```
      Source |       SS       df       MS              Number of obs =      66
-------------+------------------------------           F( 16,    49) =   39.94
       Model |  11.3454976    16  .709093599           Prob > F      =  0.0000
    Residual |  .870025443    49  .017755621           R-squared     =  0.9288
-------------+------------------------------           Adj R-squared =  0.9055
       Total |   12.215523    65  .187931123           Root MSE      =  .13325

------------------------------------------------------------------------------
        peak |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
avg_peak_~65 |   .0268906   .0083923     3.20   0.002     .0100256    .0437555
avg_prepe~65 |   .0117585    .009868     1.19   0.239    -.0080719     .031589
         thi |   .0449338   .0148317     3.03   0.004     .0151283    .0747392
    thi_lag1 |   .0176791    .006972     2.54   0.014     .0036684    .0316899
         dt2 |   .0728492   .0539436     1.35   0.183    -.0355545    .1812528
         dt3 |  -.0065675     .05478    -0.12   0.905     -.116652     .103517
         dt4 |  -.0257056   .0545225    -0.47   0.639    -.1352727    .0838615
         dt5 |   .0417217   .0612681     0.68   0.499    -.0814011    .1648445
          m7 |   .0367566   .0502359     0.73   0.468    -.0641963    .1377094
          m8 |  -.0668068   .0462698    -1.44   0.155    -.1597895    .0261759
      event1 |   -.291169     .14386    -2.02   0.048    -.5802664   -.0020715
      event2 |  -.2458629    .152681    -1.61   0.114    -.5526869    .0609612
      event3 |  -.6284605   .1462753    -4.30   0.000    -.9224116   -.3345093
      event4 |  -.2409599   .1476751    -1.63   0.109    -.5377242    .0558044
      event5 |  -.3956933   .1444886    -2.74   0.009    -.6860541   -.1053326
      event6 |  -.5082002   .1428656    -3.56   0.001    -.7952994   -.2211009
       _cons |  -3.481105    1.00878    -3.45   0.001    -5.508325   -1.453886
------------------------------------------------------------------------------
```

Table 5-4 Estimated Elasticities of Substitution, by Rate and Event/Price Level

The output tables below contain results of Generalized Leontief models when estimated using data for customers identified as responders, aggregated by rate type (CPP, PTR, and RTP only). Each model is a non-liner regression specified according to the equation in Chapter 5 of the report. The values displayed in Table 5-4 of the report are derived using the methodology outlined in Appendix A. Appendix A also defines the variable labels found in the tables below.

- **CPP reponders**

```
      Source |       SS       df       MS
-------------+------------------------------         Number of obs =        66
       Model |  89.9284083     4  22.4821021         R-squared     =    0.9957
    Residual |  .385955713    62  .006225092         Adj R-squared =    0.9955
-------------+------------------------------         Root MSE      =  .0788993
       Total |   90.314364    66  1.36839945         Res. dev.     = -152.0515

------------------------------------------------------------------------------
ln_es_p_es_o |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         /cd |   .0053311   .0032069     1.66   0.101    -.0010793    .0117416
         /hp |    .000698   .0007309     0.95   0.343    -.0007631     .002159
        /gpp |   .1310393    .006779    19.33   0.000     .1174882    .1445904
        /gpo |   .0416658   .0054163     7.69   0.000     .0308388    .0524928
------------------------------------------------------------------------------

------------------------------------------------------------------------------
ln_es_p_es_o |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         goo |   .7856291   .0060117   130.68   0.000     .7736119    .7976462
------------------------------------------------------------------------------
```

- **PTR reponders**

```
      Source |       SS       df       MS
-------------+------------------------------         Number of obs =        66
       Model |  93.9415124     4  23.4853781         R-squared     =    0.9935
    Residual |   .61394514    62  .009902341         Adj R-squared =    0.9931
-------------+------------------------------         Root MSE      =  .0995105
       Total |  94.5554575    66  1.43265845         Res. dev.     = -121.4154

------------------------------------------------------------------------------
ln_es_p_es_o |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         /cd |   .0054963   .0040248     1.37   0.177    -.0025491    .0135417
         /hp |  -.0000799    .000987    -0.08   0.936     -.002053    .0018932
        /gpp |    .138414   .0089427    15.48   0.000     .1205377    .1562902
        /gpo |   .0375223   .0070643     5.31   0.000      .023401    .0516436
------------------------------------------------------------------------------

------------------------------------------------------------------------------
ln_es_p_es_o |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         goo |   .7865414   .0077067   102.06   0.000     .7711358     .801947
------------------------------------------------------------------------------
```

- **RTP reponders**

```
      Source |       SS       df       MS
-------------+------------------------------         Number of obs =        66
```

Model	75.8142362	4	18.953559	R-squared =	0.9951
Residual	.376720008	62	.006076129	Adj R-squared =	0.9947
				Root MSE =	.0779495
Total	76.1909562	66	1.15440843	Res. dev. =	-153.65

ln_es_p_es_o	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
/cd	.0097911	.0040171	2.44	0.018	.001761	.0178211
/hp	.0003697	.0008309	0.44	0.658	-.0012912	.0020306
/gpp	.1115804	.0386729	2.89	0.005	.0342744	.1888865
/gpo	.0754897	.0427639	1.77	0.082	-.0099941	.1609735

ln_es_p_es_o	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
goo	.7374401	.0471846	15.63	0.000	.6431196	.8317607

Table 5-5 Dependence of the Natural Log of Monthly Usage on IBR Status

Table 5-5 contains results of a linear regression model in which the dependent variable is the natural log of kW usage during a specific billing month averaged across customers in the IBR treatment cells (ln_avg_usage). There is one observation for each of billing months six through nine in 2009 and 2010.

Source	SS	df	MS		
				Number of obs =	8
				F(2, 5) =	248.73
Model	.343265852	2	.171632926	Prob > F =	0.0000
Residual	.003450204	5	.000690041	R-squared =	0.9900
				Adj R-squared =	0.9861
Total	.346716056	7	.049530865	Root MSE =	.02627

ln_avg_usage	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
weighted_cdd	.0630906	.0039878	15.82	0.000	.0528396	.0733416
ibr	.0157728	.0254931	0.62	0.563	-.0497594	.081305
_cons	6.18898	.0221916	278.89	0.000	6.131935	6.246026

Appendix D Tables

Table D-1 Impacts of Rate Type on Opt Outs

Table D-1 contains the results of a logistic regression where the dependent variable is a binary choice variable that equals one if the customer opted out of the pilot program and zero otherwise. There is one observation per customer and customers are excluded from the analysis if they receive no education (i.e., treatment cell F1) or if they finaled (e.g., moved out of the residence) before or during the pilot program. Because all customers who opted out of the program received full education, a coefficient could not be estimated for the full_educ variable and basic education customers (i.e. those in cell F3) were not included in the regression. The control group consists of customers with the IBR rate treatment and eWeb technology (i.e., treatment cell E1).

Number of obs	=	7083
LR chi2(13)	=	75.58
Prob > chi2	=	0.0000

Log likelihood = -723.06176 Pseudo R2 = 0.0497

optout	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
cpp	2.225703	.5948054	3.74	0.000	1.059906	3.391501
dap	1.39907	.6269082	2.23	0.026	.1703528	2.627788
flr	-.629374	.9188281	-0.68	0.493	-2.430244	1.171496
ptr	1.830285	.6105519	3.00	0.003	.633625	3.026945
tou	1.640943	.6222085	2.64	0.008	.4214365	2.860449
bihd	.5991004	.2448144	2.45	0.014	.119273	1.078928
aihd	.1413763	.2794519	0.51	0.613	-.4063393	.6890918
pct	.2363723	.3095123	0.76	0.445	-.3702608	.8430053
bill_prot	.3438761	.3778669	0.91	0.363	-.3967294	1.084482
purch_tech	.155429	.3839439	0.40	0.686	-.5970873	.9079453
full_educ	(omitted)					
SFSH	.4215452	1.034746	0.41	0.684	-1.606519	2.449609
MFNS	-.4319955	.1883251	-2.29	0.022	-.8011059	-.0628851
MFSH	.5105014	.4319673	1.18	0.237	-.336139	1.357142
_cons	-5.674732	.6089401	-9.32	0.000	-6.868232	-4.481231

Table D-2 Impacts of Rate Type on Electricity Usage

Table D-2 contains results from a linear regression model using robust standard errors where the dependent variable is usage. There is one observation per customer; and customers are excluded if they are in treatment cells F1 or F2, are in any of the IBR treatment cells, or are screened due to data problems discussed in the report. The control group consists of customers in treatment cell F3 residing in single-family homes with non-space heating.

Number of obs = 5262
F(13, 5248) = 124.34
Prob > F = 0.0000
R-squared = 0.1936
Root MSE = .73794

usage	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
cpp	.0105061	.0396595	0.26	0.791	-.067243	.0882552
dap	.0500449	.0431413	1.16	0.246	-.03453	.1346197
ptr	.0107828	.0428695	0.25	0.801	-.0732592	.0948248
tou	.0532086	.0432238	1.23	0.218	-.0315281	.1379453
bihd	-.0167791	.0273173	-0.61	0.539	-.0703325	.0367742
aihd	.0326648	.0315776	1.03	0.301	-.0292404	.09457
pct	.0133519	.0392238	0.34	0.734	-.0635431	.0902469
bill_prot	.0281828	.0481903	0.58	0.559	-.0662903	.1226559
purch_tech	-.0570161	.048354	-1.18	0.238	-.1518101	.0377778
full_educ	-.0609152	.0648714	-0.94	0.348	-.1880902	.0662597
SFSH	.0641051	.1948932	0.33	0.742	-.3179666	.4461768
MFNS	-.7438072	.0186541	-39.87	0.000	-.7803769	-.7072375
MFSH	-.6968371	.0797475	-8.74	0.000	-.8531754	-.5404987
_cons	1.503251	.0532852	28.21	0.000	1.39879	1.607712

Table D-3 Impacts of Rate Type on Summer Peak Load

Table D-3 contains results from the two models detailed below. Each model contains one observation per customer; and customers are excluded if they are in treatment cells F1 or F2, are in any of the IBR treatment cells, or are screened due to data problems discussed in the report. The control group consists of customers in treatment cell F3 residing in single-family homes with non-space heating.

- Linear regression model using robust standard errors where the dependent variable is `peak`.

```
Number of obs =    5262
F( 13,  5248) =  137.43
Prob > F      =  0.0000
R-squared     =  0.2056
Root MSE      =  .92855
```

peak	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
cpp	.0435275	.0461808	0.94	0.346	-.047006	.134061
dap	.1149525	.0521365	2.20	0.028	.0127432	.2171617
ptr	.0464339	.0509584	0.91	0.362	-.0534657	.1463336
tou	.0645381	.0511321	1.26	0.207	-.0357022	.1647783
bihd	-.0151454	.0349729	-0.43	0.665	-.0837068	.0534161
aihd	.0434226	.0391066	1.11	0.267	-.0332427	.1200879
pct	-.0171761	.047162	-0.36	0.716	-.1096332	.075281
bill_prot	.0492972	.0626946	0.79	0.432	-.0736102	.1722047
purch_tech	-.0538631	.0620194	-0.87	0.385	-.175447	.0677208
full_educ	-.0982762	.0799573	-1.23	0.219	-.2550258	.0584734
SFSH	.1420366	.2560194	0.55	0.579	-.3598679	.6439411
MFNS	-.9692645	.0232692	-41.65	0.000	-1.014882	-.9236472
MFSH	-.9352494	.0546189	-17.12	0.000	-1.042325	-.8281736
_cons	1.727603	.0670352	25.77	0.000	1.596186	1.85902

- Linear regression model using robust standard errors where the dependent variable is `event_peak`.

```
Number of obs =    5262
F( 13,  5248) =  141.95
Prob > F      =  0.0000
R-squared     =  0.2121
Root MSE      =  1.2411
```

event_peak	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
cpp	-.025466	.0623985	-0.41	0.683	-.1477932	.0968611
dap	.10446	.0699721	1.49	0.136	-.0327144	.2416344
ptr	.015013	.0688148	0.22	0.827	-.1198926	.1499186
tou	.0511518	.0694691	0.74	0.462	-.0850366	.1873401
bihd	-.0082411	.0461322	-0.18	0.858	-.0986793	.0821972
aihd	.0732734	.0520625	1.41	0.159	-.0287907	.1753375
pct	-.0187144	.0629698	-0.30	0.766	-.1421615	.1047327
bill_prot	.0736126	.0834287	0.88	0.378	-.0899424	.2371676
purch_tech	-.082295	.0803425	-1.02	0.306	-.2397998	.0752098
full_educ	-.2093572	.114258	-1.83	0.067	-.4333504	.014636
SFSH	-.0656791	.3114828	-0.21	0.833	-.676315	.5449568
MFNS	-1.317351	.031092	-42.37	0.000	-1.378304	-1.256398

MFSH	-1.292809	.0718369	-18.00	0.000	-1.433639	-1.151979
_cons	2.390548	.0987947	24.20	0.000	2.19687	2.584227

Table D-4 Impacts of Rate Type on Peak to Off-Peak Load Ratios

Table D-4 contains results from a linear regression model using robust standard errors where the dependent variable is peak_offpeak. There is one observation per customer; and customers are excluded if they are in treatment cells F1 or F2, are in any of the IBR treatment cells, or are screened due to data problems discussed in the report. The control group consists of customers in treatment cell F3 residing in single-family homes with non-space heating.

```
                                                  Number of obs =    5262
                                                  F( 13,  5248) =   31.54
                                                  Prob > F      =  0.0000
                                                  R-squared     =  0.0686
                                                  Root MSE      =  .31928
```

peak_offpeak	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
cpp	.0067588	.0166028	0.41	0.684	-.0257897	.0393073
dap	.0415613	.018171	2.29	0.022	.0059387	.0771839
ptr	.013082	.0178093	0.73	0.463	-.0218316	.0479956
tou	-.0112384	.0175368	-0.64	0.522	-.0456178	.0231411
bihd	.0021658	.0123434	0.18	0.861	-.0220325	.026364
aihd	.0113001	.0135136	0.84	0.403	-.0151921	.0377923
pct	-.0123764	.0173329	-0.71	0.475	-.0463561	.0216034
bill_prot	.0350579	.0217039	1.62	0.106	-.0074909	.0776067
purch_tech	.0036473	.0199347	0.18	0.855	-.0354331	.0427277
full_educ	-.004837	.0294512	-0.16	0.870	-.0625737	.0528997
SFSH	.0767609	.0736564	1.04	0.297	-.0676363	.2211581
MFNS	-.1759992	.009092	-19.36	0.000	-.1938233	-.1581751
MFSH	-.1050703	.0318221	-3.30	0.001	-.1674549	-.0426856
_cons	1.159357	.024199	47.91	0.000	1.111917	1.206797

Table D-5 Impacts of Technology on Implementation Rates

Table D-5 contains the results of a logistic regression where the dependent variable is a binary choice variable that takes on the value of unity if the customer implemented the technology and zero otherwise (implement). There is one observation per customer; and customers are excluded if they are in treatment cell F1, are in any of the eWeb treatment cells, or are screened due to data problems discussed in the report. The control group consists of customers in treatment cells F6 and F7 residing in single-family homes with non-space heating.

```
                                             Number of obs   =       4116
                                             LR chi2(11)     =     346.95
                                             Prob > chi2     =     0.0000
Log likelihood = -1953.3632                  Pseudo R2       =     0.0816
```

implement	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
cpp	.219435	.1497925	1.46	0.143	-.074153	.513023
dap	.1404374	.1590156	0.88	0.377	-.1712275	.4521023

ptr	-.0233422	.1577168	-0.15	0.882	-.3324614	.2857769
tou	.2562746	.151836	1.69	0.091	-.0413185	.5538677
ibr	.0199715	.169589	0.12	0.906	-.3124168	.3523599
aihd	-1.17205	.100271	-11.69	0.000	-1.368577	-.9755221
pct	-.8978029	.1423426	-6.31	0.000	-1.176789	-.6188166
purch_tech	-2.775676	.3702018	-7.50	0.000	-3.501258	-2.050094
SFSH	-.0894753	.6938519	-0.13	0.897	-1.4494	1.270449
MFNS	-.4806103	.0886775	-5.42	0.000	-.654415	-.3068057
MFSH	-.2157011	.301651	-0.72	0.475	-.8069261	.375524
_cons	-.749653	.1262515	-5.94	0.000	-.9971014	-.5022047

Table D-6 Impacts of Technology on Electricity Usage *and*

Table D-7 Impacts of Technology on Peak to Off-Peak Usage Ratios

Tables D-6 and D-7 contain results for four models detailed below. These models differ from those in Table 5-1 in that they include the technology implementation indicator variables defined above. Each model contains one observation per customer; and customers are excluded if they are in treatment cells F1 or F2, are in any of the IBR treatment cells, or are screened due to data problems discussed in the report. The control group consists of customers in treatment cell F3 residing in single-family homes with non-space heating.

- Linear regression model using robust standard errors where the dependent variable is `usage`.

```
Number of obs =    5262
F( 16,  5245) =  102.64
Prob > F      =  0.0000
R-squared     =  0.1958
Root MSE      =  .73716
```

usage	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
bihd_imp	.1355209	.0379034	3.58	0.000	.0612145	.2098273
aihd_imp	.043651	.0529614	0.82	0.410	-.0601753	.1474773
pct_imp	-.1610376	.1832794	-0.88	0.380	-.5203416	.1982664
cpp	.0089053	.0396101	0.22	0.822	-.0687469	.0865576
dap	.0481854	.0430233	1.12	0.263	-.0361581	.1325289
ptr	.0112174	.042821	0.26	0.793	-.0727296	.0951644
tou	.0489826	.043234	1.13	0.257	-.035774	.1337392
bihd	-.0576937	.029411	-1.96	0.050	-.1153516	-.0000359
aihd	.02484	.0324386	0.77	0.444	-.0387533	.0884332
pct	.0099557	.0403959	0.25	0.805	-.0692372	.0891485
bill_prot	.0284572	.0481936	0.59	0.555	-.0660223	.1229367
purch_tech	-.031468	.0490835	-0.64	0.521	-.1276921	.0647561
full_educ	-.0598293	.064864	-0.92	0.356	-.1869898	.0673311
SFSH	.0657762	.1961161	0.34	0.737	-.3186931	.4502454
MFNS	-.7394339	.0187732	-39.39	0.000	-.7762371	-.7026306
MFSH	-.6960343	.0797247	-8.73	0.000	-.8523279	-.5397408
_cons	1.501886	.0533073	28.17	0.000	1.397382	1.606391

- Linear regression model using robust standard errors where the dependent variable is `peak`.

```
Number of obs =    5262
F( 16,  5245) =  112.36
Prob > F      =  0.0000
R-squared     =  0.2066
```

Root MSE = .92818

peak	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
bihd_imp	.1200622	.0493892	2.43	0.015	.0232388	.2168855
aihd_imp	.0020087	.0682717	0.03	0.977	-.1318322	.1358497
pct_imp	-.2031534	.2476804	-0.82	0.412	-.6887101	.2824032
cpp	.0427335	.0462109	0.92	0.355	-.047859	.1333261
dap	.113581	.0520912	2.18	0.029	.0114605	.2157015
ptr	.046715	.0509315	0.92	0.359	-.0531319	.1465619
tou	.061051	.0511862	1.19	0.233	-.0392953	.1613972
bihd	-.0512195	.0376278	-1.36	0.174	-.1249857	.0225466
aihd	.0407149	.0400754	1.02	0.310	-.0378496	.1192794
pct	-.0130015	.0480937	-0.27	0.787	-.1072852	.0812822
bill_prot	.0493837	.0627086	0.79	0.431	-.0735513	.1723187
purch_tech	-.0330887	.062996	-0.53	0.599	-.1565872	.0904098
full_educ	-.0975189	.0799765	-1.22	0.223	-.2543062	.0592684
SFSH	.1439057	.2569424	0.56	0.575	-.3598085	.6476199
MFNS	-.9662585	.0234091	-41.28	0.000	-1.01215	-.9203668
MFSH	-.9354611	.0545878	-17.14	0.000	-1.042476	-.8284463
_cons	1.726687	.0670665	25.75	0.000	1.595208	1.858165

- Linear regression model using robust standard errors where the dependent variable is `event_peak`.

Number of obs = 5262
F(16, 5245) = 115.97
Prob > F = 0.0000
R-squared = 0.2132
Root MSE = 1.2407

event_peak	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
bihd_imp	.159835	.0662746	2.41	0.016	.0299092	.2897607
aihd_imp	-.0192845	.0912221	-0.21	0.833	-.1981178	.1595489
pct_imp	-.2049281	.325711	-0.63	0.529	-.8434572	.433601
cpp	-.0261693	.0624226	-0.42	0.675	-.1485437	.0962051
dap	.1027739	.06992	1.47	0.142	-.0342985	.2398462
ptr	.0151465	.0687861	0.22	0.826	-.1197029	.1499958
tou	.0466358	.0694665	0.67	0.502	-.0895475	.182819
bihd	-.0561275	.0497209	-1.13	0.259	-.1536011	.0413462
aihd	.0721274	.0533149	1.35	0.176	-.032392	.1766468
pct	-.0112991	.0644036	-0.18	0.861	-.137557	.1149588
bill_prot	.0736222	.0834478	0.88	0.378	-.0899702	.2372145
purch_tech	-.0557101	.0813175	-0.69	0.493	-.2151264	.1037061
full_educ	-.2084695	.1142863	-1.82	0.068	-.4325183	.0155792
SFSH	-.0624787	.3121539	-0.20	0.841	-.6744303	.5494728
MFNS	-1.313506	.0312806	-41.99	0.000	-1.374829	-1.252183
MFSH	-1.293354	.0717287	-18.03	0.000	-1.433972	-1.152736
_cons	2.389384	.0988449	24.17	0.000	2.195607	2.583161

- Linear regression model using robust standard errors where the dependent variable is `peak_offpeak`.

Number of obs = 5262
F(16, 5245) = 26.02

```
                                                  Prob > F      =  0.0000
                                                  R-squared     =  0.0700
                                                  Root MSE      =  .31913

------------------------------------------------------------------------------
             |               Robust
peak_offpeak |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    bihd_imp |  -.0342816   .0155102    -2.21   0.027     -.064688   -.0038752
    aihd_imp |  -.0440799   .0211859    -2.08   0.038    -.0856131   -.0025467
     pct_imp |  -.0055389   .0857046    -0.06   0.948    -.1735556    .1624779
         cpp |   .0077246   .0166296     0.46   0.642    -.0248764    .0403256
         dap |   .0422783   .0181585     2.33   0.020     .0066802    .0778764
         ptr |    .012864   .0178271     0.72   0.471    -.0220846    .0478126
         tou |  -.0099402   .0175338    -0.57   0.571    -.0443136    .0244333
        bihd |   .0126745   .0134713     0.94   0.347    -.0137348    .0390839
        aihd |   .0170806   .0139042     1.23   0.219    -.0101775    .0443386
         pct |  -.0052418    .017888    -0.29   0.770    -.0403098    .0298261
   bill_prot |   .0348464   .0217094     1.61   0.109    -.0077132    .0774059
  purch_tech |  -.0044876   .0201741    -0.22   0.824    -.0440373     .035062
   full_educ |   -.005296   .0294605    -0.18   0.857    -.0630509    .0524589
        SFSH |   .0767272   .0728028     1.05   0.292    -.0659966    .2194511
        MFNS |  -.1778586   .0091288   -19.48   0.000    -.1957548   -.1599624
        MFSH |  -.1060815   .0317969    -3.34   0.001    -.1684166   -.0437464
       _cons |   1.159956   .0242049    47.92   0.000     1.112504    1.207408
------------------------------------------------------------------------------
```

Table D-8 Usage of Cells Relative to Cell F3 *and*

Table D-9 Peak to Off-Peak Usage Ratios of Cells Relative to Cell F3

Tables D-8 and D-9 contain the results of four models detailed below. Each model contains one observation per customer; and customers are excluded if they are in treatment cells F1 or F2, are in any of the IBR treatment cells, or are screened due to data problems discussed in the report. The control group consists of customers in treatment cell F3 residing in single-family homes with non-space heating.

- Linear regression model using robust standard errors where the dependent variable is `usage`.

```
                                                  Number of obs =     5262
                                                  F( 24,  5237) =    68.26
                                                  Prob > F      =  0.0000
                                                  R-squared     =  0.1958
                                                  Root MSE      =  .73773

------------------------------------------------------------------------------
             |               Robust
       usage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          d1 |  -.0567648   .0620971    -0.91   0.361    -.1785011    .0649715
         d1b |   .0519678   .0802184     0.65   0.517    -.1052937    .2092293
          d2 |  -.0904288   .0639923    -1.41   0.158    -.2158805    .0350228
          d3 |  -.0004905   .0656012    -0.01   0.994    -.1290961    .1281152
          d4 |  -.0545413   .0654397    -0.83   0.405    -.1828304    .0737478
          d5 |   .0085543   .0791117     0.11   0.914    -.1465376    .1636461
          d6 |  -.1049365   .0635947    -1.65   0.099    -.2296085    .0197356
          d7 |  -.0304105   .0814648    -0.37   0.709    -.1901155    .1292945
          d8 |   .0042864   .0726705     0.06   0.953    -.1381781     .146751
          f5 |  -.0792982   .0794064    -1.00   0.318    -.2349679    .0763714
          f6 |  -.0923322   .0701278    -1.32   0.188     -.229812    .0451475
```

```
           f7 |   .0090008   .0921952     0.10   0.922    -.1717403    .1897419
           l1 |  -.0314171   .0757977    -0.41   0.679    -.1800122     .117178
          l1b |  -.0493871   .0774266    -0.64   0.524    -.2011756    .1024014
           l2 |    .000453   .0652786     0.01   0.994    -.1275203    .1284262
           l3 |    .050097    .076059     0.66   0.510    -.0990103    .1992043
           l4 |  -.0073554   .0668315    -0.11   0.912    -.1383731    .1236623
           l5 |   .0224433   .0661297     0.34   0.734    -.1071986    .1520851
          l5b |  -.1077259   .0743837    -1.45   0.148    -.2535489    .0380972
           l6 |  -.0830706   .0744878    -1.12   0.265    -.2290978    .0629566
          l6b |  -.0057287   .0790728    -0.07   0.942    -.1607444     .149287
         SFSH |   .0726782   .1978088     0.37   0.713    -.3151097     .460466
         MFNS |  -.7440102   .0186653   -39.86   0.000     -.780602   -.7074184
         MFSH |  -.6928552   .0797989    -8.68   0.000    -.8492943   -.5364161
        _cons |     1.5032   .0533391    28.18   0.000     1.398633    1.607767
------------------------------------------------------------------------------
```

- Linear regression model using robust standard errors where the dependent variable is `peak`.

```
                                                       Number of obs =    5262
                                                       F( 24,  5237) =   75.04
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.2071
                                                       Root MSE      =   .9286

------------------------------------------------------------------------------
             |               Robust
        peak |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          d1 |  -.0780491   .0787615    -0.99   0.322    -.2324544    .0763562
         d1b |   .0858992    .105425     0.81   0.415    -.1207778    .2925761
          d2 |  -.0980179   .0812575    -1.21   0.228    -.2573164    .0612806
          d3 |   .0192516   .0829219     0.23   0.816      -.14331    .1818131
          d4 |  -.0865497   .0794247    -1.09   0.276    -.2422553    .0691558
          d5 |   .0171307   .0990824     0.17   0.863    -.1771121    .2113735
          d6 |  -.1087576   .0813406    -1.34   0.181    -.2682191    .0507039
          d7 |  -.0156698   .1055287    -0.15   0.882    -.2225501    .1912104
          d8 |    -.03462   .0913317    -0.38   0.705    -.2136683    .1444283
          f5 |  -.1057036   .0977823    -1.08   0.280    -.2973976    .0859905
          f6 |  -.1214132   .0878893    -1.38   0.167    -.2937129    .0508864
          f7 |  -.0370372   .0994972    -0.37   0.710    -.2320931    .1580188
          l1 |  -.0051937   .0962467    -0.05   0.957    -.1938774    .1834899
         l1b |  -.0161083   .0970873    -0.17   0.868    -.2064399    .1742233
          l2 |   .0396597   .0850162     0.47   0.641    -.1270076     .206327
          l3 |   .0835694   .0981692     0.85   0.395    -.1088831    .2760219
          l4 |  -.0165543   .0870597    -0.19   0.849    -.1872277     .154119
          l5 |  -.0079068   .0826691    -0.10   0.924    -.1699726    .1541591
         l5b |  -.1265416   .0938052    -1.35   0.177    -.3104389    .0573557
          l6 |  -.1012226   .0946372    -1.07   0.285     -.286751    .0843058
         l6b |  -.0202702   .1023836    -0.20   0.843    -.2209848    .1804445
        SFSH |   .1529846   .2610001     0.59   0.558    -.3586844    .6646536
        MFNS |  -.9697069    .023309   -41.60   0.000    -1.015402   -.9240115
        MFSH |  -.9312268   .0546541   -17.04   0.000    -1.038372    -.824082
       _cons |   1.727625   .0671035    25.75   0.000     1.596074    1.859175
------------------------------------------------------------------------------
```

- Linear regression model using robust standard errors where the dependent variable is `event_peak`.

```
                                                       Number of obs =    5262
                                                       F( 24,  5237) =   77.30
                                                       Prob > F      =  0.0000
```

R-squared	= 0.2136
Root MSE	= 1.2413

event_peak	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
d1	-.2441734	.1132444	-2.16	0.031	-.4661796	-.0221673
d1b	-.0618506	.1465436	-0.42	0.673	-.3491373	.225436
d2	-.3067672	.1143679	-2.68	0.007	-.530976	-.0825584
d3	-.1200575	.1190781	-1.01	0.313	-.3535001	.1133852
d4	-.2622365	.1136958	-2.31	0.021	-.4851277	-.0393453
d5	-.109509	.1349554	-0.81	0.417	-.374078	.1550599
d6	-.2495212	.1169076	-2.13	0.033	-.4787088	-.0203337
d7	-.1173498	.1459705	-0.80	0.421	-.4035128	.1688132
d8	-.1924877	.1301029	-1.48	0.139	-.4475437	.0625683
f5	-.2749237	.1341464	-2.05	0.040	-.5379065	-.0119409
f6	-.1989838	.1273831	-1.56	0.118	-.4487079	.0507403
f7	-.0962676	.1407435	-0.68	0.494	-.3721836	.1796484
l1	-.1000498	.1327991	-0.75	0.451	-.3603914	.1602919
l1b	-.1205879	.1360365	-0.89	0.375	-.3872762	.1461004
l2	-.0975369	.1194021	-0.82	0.414	-.3316149	.1365411
l3	.0213049	.1398456	0.15	0.879	-.2528509	.2954607
l4	-.1506885	.1237009	-1.22	0.223	-.3931938	.0918169
l5	-.1012242	.1187076	-0.85	0.394	-.3339406	.1314922
l5b	-.243508	.1334129	-1.83	0.068	-.5050529	.0180369
l6	-.2420274	.1316912	-1.84	0.066	-.5001969	.0161422
l6b	-.1722905	.1336385	-1.29	0.197	-.4342777	.0896967
SFSH	-.0471708	.3179806	-0.15	0.882	-.6705454	.5762039
MFNS	-1.317814	.0311491	-42.31	0.000	-1.378879	-1.256749
MFSH	-1.286536	.0721112	-17.84	0.000	-1.427904	-1.145168
_cons	2.390512	.0988979	24.17	0.000	2.196631	2.584393

- Linear regression model using robust standard errors where the dependent variable is `peak_offpeak`.

Number of obs	= 5262
F(24, 5237)	= 17.65
Prob > F	= 0.0000
R-squared	= 0.0698
Root MSE	= .31941

peak_offpeak	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
d1	-.0089529	.0282663	-0.32	0.751	-.0643665	.0464608
d1b	.0313183	.0352831	0.89	0.375	-.0378513	.1004879
d2	.0013618	.0299561	0.05	0.964	-.0573647	.0600883
d3	.0222418	.0293799	0.76	0.449	-.035355	.0798386
d4	-.0026398	.0296506	-0.09	0.929	-.0607672	.0554877
d5	.0157536	.0336067	0.47	0.639	-.0501296	.0816368
d6	.0120876	.0291824	0.41	0.679	-.0451219	.0692972
d7	.0273732	.0355735	0.77	0.442	-.0423656	.097112
d8	-.0224257	.0328338	-0.68	0.495	-.0867937	.0419422
f5	.0318494	.039431	0.81	0.419	-.0454519	.1091506
f6	-.015575	.0303976	-0.51	0.608	-.075167	.044017
f7	-.0125116	.0336292	-0.37	0.710	-.0784388	.0534156
l1	.0126441	.0325711	0.39	0.698	-.0512088	.076497
l1b	.0768896	.036694	2.10	0.036	.0049541	.1488251
l2	.0487159	.0302256	1.61	0.107	-.0105389	.1079706

l3	.0461234	.034338	1.34	0.179	-.0211934	.1134402
l4	-.0138304	.0328739	-0.42	0.674	-.078277	.0506162
l5	-.0157928	.0280962	-0.56	0.574	-.0708731	.0392876
l5b	-.0060247	.0327362	-0.18	0.854	-.0702012	.0581518
l6	-.0026266	.0329848	-0.08	0.937	-.0672905	.0620373
l6b	-.0053885	.0343575	-0.16	0.875	-.0727435	.0619664
SFSH	.0739332	.0733642	1.01	0.314	-.0698913	.2177576
MFNS	-.1760469	.009112	-19.32	0.000	-.1939102	-.1581837
MFSH	-.1060481	.0317769	-3.34	0.001	-.168344	-.0437522
_cons	1.159399	.0242258	47.86	0.000	1.111906	1.206892

Table D-11 Usage Comparisons by Method of Obtaining Technology

Table D-11 contains the results of four models detailed below. Each model contains one observation per customer; and customers are included in the sample if they are in treatment cell L5a, L5b, L6a, or L6b and were not screened due to data problems discussed in the report. The control group consists of customers in treatment cell L5a.

- Linear regression model using robust standard errors where the dependent variable is `usage`.

```
Number of obs =    1002
F(  5,   996) =   45.82
Prob > F      =  0.0000
R-squared     =  0.1408
Root MSE      =  .79207
```

usage	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
aihd	-.0192624	.0511762	-0.38	0.707	-.119688	.0811632
purch_tech	-.043538	.0510147	-0.85	0.394	-.1436468	.0565707
SFSH	-.2358391	.3021029	-0.78	0.435	-.8286703	.356992
MFNS	-.6667423	.0455747	-14.63	0.000	-.7561758	-.5773088
MFSH	-.731788	.0932124	-7.85	0.000	-.9147032	-.5488728
_cons	1.475398	.0452604	32.60	0.000	1.386581	1.564215

- Linear regression model using robust standard errors where the dependent variable is `peak`.

```
Number of obs =    1002
F(  5,   996) =   51.18
Prob > F      =  0.0000
R-squared     =  0.1473
Root MSE      =  1.0026
```

peak	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
aihd	-.0111247	.065463	-0.17	0.865	-.139586	.1173367
purch_tech	-.0344487	.064995	-0.53	0.596	-.1619915	.0930942
SFSH	-.0908329	.4832827	-0.19	0.851	-1.039202	.8575363
MFNS	-.8681878	.0564578	-15.38	0.000	-.9789777	-.757398
MFSH	-.9408796	.0998918	-9.42	0.000	-1.136902	-.744857
_cons	1.661714	.0563115	29.51	0.000	1.551211	1.772217

- Linear regression model using robust standard errors where the dependent variable is `event_peak`.

```
                                                    Number of obs =    1002
                                                    F(  5,   996) =   55.86
                                                    Prob > F      =  0.0000
                                                    R-squared     =  0.1603
                                                    Root MSE      =  1.3226

------------------------------------------------------------------------------
             |               Robust
  event_peak |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        aihd |  -.0534031   .0849021    -0.63   0.529    -.2200105    .1132043
  purch_tech |  -.0527612   .0852519    -0.62   0.536    -.2200552    .1145329
        SFSH |  -.3117356   .7748975    -0.40   0.688    -1.832355    1.208883
        MFNS |  -1.201885   .0743348   -16.17   0.000    -1.347755   -1.056014
        MFSH |  -1.306125   .1402871    -9.31   0.000    -1.581417   -1.030833
       _cons |   2.225081   .0771374    28.85   0.000     2.073711    2.376452
------------------------------------------------------------------------------
```

- Linear regression model using robust standard errors where the dependent variable is `peak_offpeak`.

```
                                                    Number of obs =    1002
                                                    F(  5,   996) =   11.46
                                                    Prob > F      =  0.0000
                                                    R-squared     =  0.0515
                                                    Root MSE      =  .31142

------------------------------------------------------------------------------
             |               Robust
peak_offpeak |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        aihd |   .0084195   .0209128     0.40   0.687    -.0326186    .0494576
  purch_tech |   .0054689   .0208338     0.26   0.793    -.0354142    .0463519
        SFSH |   .1945361    .152427     1.28   0.202    -.1045788    .4936509
        MFNS |  -.1489912   .0204591    -7.28   0.000    -.1891392   -.1088432
        MFSH |  -.1495793   .0781777    -1.91   0.056    -.3029912    .0038326
       _cons |   1.136002   .0154087    73.72   0.000     1.105765    1.166239
------------------------------------------------------------------------------
```

Table D-12 Impact of Bill Protection on Opt-Out Rates

Table D-12 contains the results of a logistic regression where the dependent variable is optout. There is one observation per customer; and customers are included in the sample if they are in treatment cells D1a, D1b, L1a, or L1b and did not final before or during the pilot program. Because there are no customers who opted out of the pilot program with either SFSH or MFSH housing, coefficients could not be estimated for these variables and customers with SFSH or MFSH housing were not included in the regression. The control group consists of customers in treatment cell D1 residing in single-family homes with non-space heating.

```
                                                  Number of obs   =       1092
                                                  LR chi2(3)      =       5.75
                                                  Prob > chi2     =     0.1243
Log likelihood = -127.34121                       Pseudo R2       =     0.0221

------------------------------------------------------------------------------
      optout |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
```

```
-------------+----------------------------------------------------------------
         dap |  -.8000119   .4712447    -1.70   0.090    -1.723634    .1236108
   bill_prot |   .2232355   .3981498     0.56   0.575    -.5571237    1.003595
        SFSH |  (omitted)
        MFNS |  -.6205002   .4418361    -1.40   0.160    -1.486483    .2454826
        MFSH |  (omitted)
       _cons |  -3.293355   .2816838   -11.69   0.000    -3.845445   -2.741265
------------------------------------------------------------------------------
```

Table D-13 Usage Comparisons by Notification of Bill Protection

Table D-13 contains the results of four models detailed below. Each model contains one observation per customer; and customers are included in the sample if they are in treatment cells D1a, D1b, L1a, or L1b and were not screened due to data problems discussed in the report. The control group consists of customers in treatment cell L1a residing in single-family homes with non-space heating.

- Linear regression model using robust standard errors where the dependent variable is `usage`.

```
                                                       Number of obs =     872
                                                       F(  5,   866) =   60.33
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.2224
                                                       Root MSE      =  .69469

------------------------------------------------------------------------------
             |               Robust
       usage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         cpp |    .023537   .0509593     0.46   0.644    -.0764812    .1235552
   bill_prot |   .0555766   .0519671     1.07   0.285    -.0464197    .1575728
        SFSH |   .5757332    .255125     2.26   0.024     .0749974    1.076469
        MFNS |  -.7415597   .0449383   -16.50   0.000    -.8297605   -.6533589
        MFSH |  -.7089182   .0848792    -8.35   0.000    -.8755111   -.5423252
       _cons |   1.434666   .0559638    25.64   0.000     1.324825    1.544506
------------------------------------------------------------------------------
```

- Linear regression model using robust standard errors where the dependent variable is `peak`.

```
                                                       Number of obs =     872
                                                       F(  5,   866) =   63.56
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.2345
                                                       Root MSE      =  .89945

------------------------------------------------------------------------------
             |               Robust
        peak |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         cpp |  -.0060611    .065823    -0.09   0.927    -.1352522    .1231301
   bill_prot |   .0896896   .0679439     1.32   0.187    -.0436644    .2230436
        SFSH |   .7285287   .5446142     1.34   0.181    -.3403893    1.797447
        MFNS |  -.9960275    .056919   -17.50   0.000    -1.107743   -.8843123
        MFSH |  -.9352934   .1063002    -8.80   0.000     -1.14393   -.7266574
       _cons |   1.683435    .072335    23.27   0.000     1.541463    1.825408
------------------------------------------------------------------------------
```

- Linear regression model using robust standard errors where the dependent variable is `event_peak`.

```
                                                      Number of obs =     872
                                                      F(  5,   866) =   62.27
                                                      Prob > F      =  0.0000
                                                      R-squared     =  0.2303
                                                      Root MSE      =  1.2003

------------------------------------------------------------------------------
             |               Robust
  event_peak |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         cpp |  -.0644654   .0869396    -0.74   0.459    -.2351023    .1061715
   bill_prot |   .0956045    .090318     1.06   0.290    -.0816632    .2728722
        SFSH |   .4333573   .5938304     0.73   0.466    -.7321579    1.598872
        MFNS |  -1.322517   .0760048   -17.40   0.000    -1.471692   -1.173342
        MFSH |  -1.242124   .1535498    -8.09   0.000    -1.543497   -.9407504
       _cons |    2.23295   .0943069    23.68   0.000     2.047853    2.418046
------------------------------------------------------------------------------
```

- Linear regression model using robust standard errors where the dependent variable is `peak_offpeak`.

```
                                                      Number of obs =     872
                                                      F(  5,   866) =   17.91
                                                      Prob > F      =  0.0000
                                                      R-squared     =  0.0853
                                                      Root MSE      =  .30799

------------------------------------------------------------------------------
             |               Robust
peak_offpeak |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         cpp |  -.0315856   .0219213    -1.44   0.150    -.0746106    .0114394
   bill_prot |   .0506467   .0228241     2.22   0.027     .0058497    .0954438
        SFSH |   .0592592   .1896286     0.31   0.755    -.3129262    .4314446
        MFNS |  -.1824133   .0210257    -8.68   0.000    -.2236806   -.1411461
        MFSH |  -.1330194   .0648765    -2.05   0.041    -.2603531   -.0056858
       _cons |   1.182446   .0217613    54.34   0.000     1.139735    1.225158
------------------------------------------------------------------------------
```

Table D-14 Impact of Customer Education on Usage and

Table D-15 Impact of Customer Education on Peak to Off-Peak Usage Ratios

Tables D-14 and D-15 contain results for four models detailed below. Each model contains one observation per customer; and customers are included in the sample if they are in treatment cells F1 or F2 and were not screened due to data problems discussed in the report. Customers in treatment cell F1 residing in single-family homes with non-space heating serve as the control group.

- Linear regression model using robust standard errors where the dependent variable is `usage`.

```
                                                      Number of obs =     582
                                                      F(  4,   577) =    6.92
                                                      Prob > F      =  0.0000
                                                      R-squared     =  0.0514
                                                      Root MSE      =  1.9217

------------------------------------------------------------------------------
             |               Robust
```

```
       usage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          f2 |    -.03952   .1572887    -0.25   0.802    -.3484482    .2694082
        SFSH |   .7153181   .2508963     2.85   0.005     .2225368      1.2081
        MFNS |  -.5863848   .2016228    -2.91   0.004    -.9823889   -.1903806
        MFSH |  -.3263033   .1962968    -1.66   0.097    -.7118467    .0592402
       _cons |   2.187371    .131028    16.69   0.000     1.930021    2.444721
------------------------------------------------------------------------------
```

- Linear regression model using robust standard errors where the dependent variable is `peak`.

```
                                                       Number of obs =     582
                                                        F(  4,   577) =    8.50
                                                        Prob > F      =  0.0000
                                                        R-squared     =  0.0606
                                                        Root MSE      =  2.3876

------------------------------------------------------------------------------
             |               Robust
        peak |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          f2 |  -.0437665   .1931357    -0.23   0.821    -.4231012    .3355682
        SFSH |   .7167297   .3212771     2.23   0.026     .0857145    1.347745
        MFNS |  -.8945168   .2543688    -3.52   0.000    -1.394119   -.3949151
        MFSH |  -.7489572   .2435181    -3.08   0.002    -1.227247   -.2706671
       _cons |   2.714667   .1713667    15.84   0.000     2.378088    3.051245
------------------------------------------------------------------------------
```

- Linear regression model using robust standard errors where the dependent variable is `event_peak`.

```
                                                       Number of obs =     582
                                                        F(  4,   577) =    9.18
                                                        Prob > F      =  0.0000
                                                        R-squared     =  0.0608
                                                        Root MSE      =  2.9519

------------------------------------------------------------------------------
             |               Robust
  event_peak |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          f2 |  -.0250031   .2389891    -0.10   0.917    -.4943977    .4443916
        SFSH |    .547672   .3793432     1.44   0.149    -.1973898    1.292734
        MFNS |  -1.291119   .3336965    -3.87   0.000    -1.946527   -.6357108
        MFSH |  -1.179125   .3079803    -3.83   0.000    -1.784024   -.5742257
       _cons |   3.551686   .2244271    15.83   0.000     3.110892    3.992479
------------------------------------------------------------------------------
```

- Linear regression model using robust standard errors where the dependent variable is `peak_offpeak`.

```
                                                       Number of obs =     582
                                                        F(  4,   577) =    7.74
                                                        Prob > F      =  0.0000
                                                        R-squared     =  0.0482
                                                        Root MSE      =  .34057

------------------------------------------------------------------------------
             |               Robust
peak_offpeak |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
```

f2	.0279803	.0312744	0.89	0.371	-.0334453	.0894059
SFSH	-.0729136	.0385089	-1.89	0.059	-.1485484	.0027212
MFNS	-.1514888	.0403759	-3.75	0.000	-.2307906	-.0721871
MFSH	-.1832674	.0378515	-4.84	0.000	-.2576108	-.108924
_cons	1.291213	.0286442	45.08	0.000	1.234953	1.347472

Table D-16 Impact of Technology and Customer Education Usage and

Table D-17 Impact of Technology and Customer Education on Peak to Off-Peak Usage Ratios

Tables D-16 and D-17 contain results for four models detailed below. Each model contains one observation per customer; and customers are included in the sample if they are in treatment cell F3 or if they do not pay a flat or IBR rate for electricity and have an AMI-enabled, enabling technology (cells D2, D3, D4, D6, D7, D8, L2, L3, L5a, and L6a) and they were not screened due to data problems discussed in the report. The control group consists of all customers not in treatment cell F3 that reside in single-family homes with non-space heating.

- Linear regression model using robust standard errors where the dependent variable is `usage`.

```
                                                  Number of obs =    3435
                                                  F(  4,  3430) =  269.29
                                                  Prob > F      =  0.0000
                                                  R-squared     =  0.1955
                                                  Root MSE      =   .7356
```

usage	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
f3	.0347505	.0540891	0.64	0.521	-.0712996	.1408005
SFSH	-.026736	.2357829	-0.11	0.910	-.4890252	.4355531
MFNS	-.7493308	.0232472	-32.23	0.000	-.7949105	-.703751
MFSH	-.7611705	.0570764	-13.34	0.000	-.8730777	-.6492633
_cons	1.472023	.018566	79.29	0.000	1.435621	1.508424

- Linear regression model using robust standard errors where the dependent variable is `peak`.

```
                                                  Number of obs =    3435
                                                  F(  4,  3430) =  289.51
                                                  Prob > F      =  0.0000
                                                  R-squared     =  0.2002
                                                  Root MSE      =  .93918
```

peak	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
f3	.0393447	.0680574	0.58	0.563	-.0940924	.1727818
SFSH	.0166628	.2974925	0.06	0.955	-.5666176	.5999432
MFNS	-.9734074	.0290134	-33.55	0.000	-1.030293	-.9165221
MFSH	-.9434686	.0676937	-13.94	0.000	-1.076193	-.8107444
_cons	1.689763	.0241278	70.03	0.000	1.642457	1.737069

- Linear regression model using robust standard errors where the dependent variable is `event_peak`.

```
                                                  Number of obs =    3435
                                                  F(  4,  3430) =  301.74
                                                  Prob > F      =  0.0000
                                                  R-squared     =  0.2073
                                                  Root MSE      =  1.2543

------------------------------------------------------------------------------
             |               Robust
  event_peak |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          f3 |   .1786944   .0995861     1.79   0.073    -.0165596    .3739484
        SFSH |  -.1479051   .3810686    -0.39   0.698    -.8950495    .5992392
        MFNS |  -1.326807   .0386496   -34.33   0.000    -1.402585   -1.251028
        MFSH |  -1.272517   .0900521   -14.13   0.000    -1.449079   -1.095956
       _cons |   2.214179   .0320853    69.01   0.000      2.15127    2.277087
------------------------------------------------------------------------------
```

- Linear regression model using robust standard errors where the dependent variable is `peak_offpeak`.

```
                                                  Number of obs =    3435
                                                  F(  4,  3430) =   68.38
                                                  Prob > F      =  0.0000
                                                  R-squared     =  0.0690
                                                  Root MSE      =  .32005

------------------------------------------------------------------------------
             |               Robust
peak_offpeak |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          f3 |  -.0090275   .0246017    -0.37   0.714    -.0572631    .0392081
        SFSH |   .0513664   .0786841     0.65   0.514    -.1029061    .2056389
        MFNS |  -.1832443   .0111341   -16.46   0.000    -.2050745   -.1614141
        MFSH |  -.0794094   .0428338    -1.85   0.064    -.1633917    .0045729
       _cons |   1.169878    .007311   160.02   0.000     1.155544    1.184212
------------------------------------------------------------------------------
```

Table D-18 Impact of Technology and Customer Education on Usage and

Table D-19 Impact of Technology and Customer Education on Peak to Off-Peak Usage Ratios

Tables D-18 and D-19 contain results for four models detailed below. Each model contains one observation per customer; and customers are included in the sample if they face the flat rate and have an AMI-enabled enabling technology (treatment cells F6 and F7) or have an AMI-enabled enabling technology but who do not pay a flat rate (treatment cells D2, D3, D4, D6, D7, D8, L2, L3, L5a, and L6a). Customers were excluded if they had data problems discussed in the report. The control group consists of customers in the sample described above, residing in single-family homes with non-space heating, and in treatment cells other than F6 or F7.

- Linear regression model using robust standard errors where the dependent variable is `usage`.

```
                                                  Number of obs =    3689
                                                  F(  4,  3684) =  288.39
                                                  Prob > F      =  0.0000
                                                  R-squared     =  0.1880
                                                  Root MSE      =   .7543
```

usage	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf. Interval]	
f6_or_f7	-.0144819	.0439061	-0.33	0.742	-.1005645	.0716007
SFSH	-.0274283	.2357575	-0.12	0.907	-.4896563	.4347998
MFNS	-.7570213	.0223409	-33.89	0.000	-.800823	-.7132196
MFSH	-.6599329	.129368	-5.10	0.000	-.9135728	-.4062929
_cons	1.472715	.0183916	80.08	0.000	1.436656	1.508774

- Linear regression model using robust standard errors where the dependent variable is `peak`.

```
Number of obs =    3689
F(  4,  3684) =  313.13
Prob > F      =  0.0000
R-squared     =  0.1989
Root MSE      =   .9437
```

peak	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf. Interval]	
f6_or_f7	-.0457435	.0488271	-0.94	0.349	-.1414744	.0499874
SFSH	.0157087	.2974415	0.05	0.958	-.5674575	.598875
MFNS	-.9763079	.027836	-35.07	0.000	-1.030883	-.9217324
MFSH	-.9399142	.0713144	-13.18	0.000	-1.079734	-.8000946
_cons	1.690717	.0236781	71.40	0.000	1.644294	1.73714

- Linear regression model using robust standard errors where the dependent variable is `event_peak`.

```
Number of obs =    3689
F(  4,  3684) =  328.02
Prob > F      =  0.0000
R-squared     =  0.2064
Root MSE      =  1.2613
```

event_peak	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf. Interval]	
f6_or_f7	.0240637	.0676268	0.36	0.722	-.108526	.1566533
SFSH	-.1512919	.3810006	-0.40	0.691	-.8982847	.5957009
MFNS	-1.33511	.0372168	-35.87	0.000	-1.408078	-1.262143
MFSH	-1.295098	.0882568	-14.67	0.000	-1.468135	-1.122061
_cons	2.217565	.0314978	70.40	0.000	2.155811	2.27932

- Linear regression model using robust standard errors where the dependent variable is `peak_offpeak`.

```
Number of obs =    3689
F(  4,  3684) =   68.59
Prob > F      =  0.0000
R-squared     =  0.0661
Root MSE      =  .31824
```

peak_offpeak	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf. Interval]	

f6_or_f7	-.0227666	.0157045	-1.45	0.147	-.053557	.0080239
SFSH	.0528872	.078671	0.67	0.501	-.1013557	.2071302
MFNS	-.1774522	.0107796	-16.46	0.000	-.1985867	-.1563176
MFSH	-.105712	.0403499	-2.62	0.009	-.1848224	-.0266016
_cons	1.168357	.0072106	162.03	0.000	1.15422	1.182494

Table D-20 Impact of Notification on Usage and

Table D-21 Impact of Notification on Peak to Off-Peak Usage Ratio

Tables D-19 and D-20 contain results for four models detailed below. Each model contains one observation per customer; and customers are excluded if they are in treatment cells F1 or F2, are in any of the IBR treatment cells, or are screened due to data problems discussed in the report. The control group consists of customers in treatment cell F3 residing in single-family homes with non-space heating.

- Linear regression model using robust standard errors where the dependent variable is `usage`.

```
Number of obs =    5262
F( 14,  5247) =  117.09
Prob > F      =  0.0000
R-squared     =  0.1978
Root MSE      =  .73612
```

usage	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
cpp	.0078763	.0394766	0.20	0.842	-.0695143	.0852669
dap	.0498639	.0429488	1.16	0.246	-.0343335	.1340614
ptr	.0116688	.0426885	0.27	0.785	-.0720183	.095356
tou	.0540929	.0430597	1.26	0.209	-.030322	.1385078
bihd	-.0197684	.0272058	-0.73	0.467	-.0731029	.0335662
aihd	.0289851	.0315122	0.92	0.358	-.032792	.0907622
pct	.0129477	.0392127	0.33	0.741	-.0639255	.0898209
bill_prot	.0235027	.0479783	0.49	0.624	-.0705549	.1175602
purch_tech	-.0586772	.0482647	-1.22	0.224	-.153296	.0359417
notify_share	.1410062	.0252332	5.59	0.000	.0915387	.1904737
full_educ	-.1654259	.06675	-2.48	0.013	-.2962838	-.034568
SFSH	.04398	.1930569	0.23	0.820	-.3344919	.4224519
MFNS	-.74152	.0186151	-39.83	0.000	-.7780132	-.7050267
MFSH	-.6884286	.0795244	-8.66	0.000	-.8443295	-.5325276
_cons	1.50231	.0532872	28.19	0.000	1.397845	1.606776

- Linear regression model using robust standard errors where the dependent variable is `peak`.

```
Number of obs =    5262
F( 14,  5247) =  129.01
Prob > F      =  0.0000
R-squared     =  0.2096
Root MSE      =  .92627
```

peak	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
cpp	.0402257	.0459409	0.88	0.381	-.0498376	.130289
dap	.1147252	.0519251	2.21	0.027	.0129305	.21652
ptr	.0475464	.0507	0.94	0.348	-.0518468	.1469396

tou	.0656483	.0509303	1.29	0.197	-.0341963	.1654929
bihd	-.0188983	.0348362	-0.54	0.588	-.0871918	.0493951
aihd	.0388027	.0390201	0.99	0.320	-.0376929	.1152983
pct	-.0176835	.0471416	-0.38	0.708	-.1101006	.0747336
bill_prot	.0434213	.0625117	0.69	0.487	-.0791275	.1659702
purch_tech	-.0559485	.0619031	-0.90	0.366	-.1773043	.0654072
notify_share	.177034	.0315499	5.61	0.000	.115183	.2388849
full_educ	-.2294899	.0826314	-2.78	0.006	-.3914819	-.0674979
SFSH	.1167694	.2543228	0.46	0.646	-.3818091	.6153479
MFNS	-.9663929	.0232136	-41.63	0.000	-1.011901	-.9208846
MFSH	-.9246925	.0541716	-17.07	0.000	-1.030891	-.8184935
_cons	1.726422	.0670335	25.75	0.000	1.595009	1.857836

- Linear regression model using robust standard errors where the dependent variable is `event_peak`.

```
Number of obs =    5262
F( 14,  5247) =  133.42
Prob > F      =  0.0000
R-squared     =  0.2166
Root MSE      =  1.2377
```

event_peak	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
cpp	-.0301322	.0620545	-0.49	0.627	-.1517849	.0915205
dap	.1041389	.0696868	1.49	0.135	-.0324762	.240754
ptr	.0165851	.0684382	0.24	0.809	-.1175822	.1507525
tou	.0527208	.0691773	0.76	0.446	-.0828954	.188337
bihd	-.0135448	.0459367	-0.29	0.768	-.1035998	.0765103
aihd	.0667445	.0519064	1.29	0.199	-.0350136	.1685026
pct	-.0194315	.0629765	-0.31	0.758	-.1428917	.1040286
bill_prot	.0653088	.0831936	0.79	0.432	-.0977852	.2284028
purch_tech	-.0852421	.0801243	-1.06	0.287	-.2423192	.0718349
notify_share	.2501843	.0422836	5.92	0.000	.167291	.3330777
full_educ	-.3947884	.1177401	-3.35	0.001	-.625608	-.1639687
SFSH	-.1013867	.3094071	-0.33	0.743	-.7079534	.50518
MFNS	-1.313293	.0310173	-42.34	0.000	-1.3741	-1.252486
MFSH	-1.27789	.0716071	-17.85	0.000	-1.41827	-1.137511
_cons	2.388879	.0988043	24.18	0.000	2.195182	2.582577

- Linear regression model using robust standard errors where the dependent variable is `peak_offpeak`.

```
Number of obs =    5262
F( 14,  5247) =   29.73
Prob > F      =  0.0000
R-squared     =  0.0690
Root MSE      =  .31924
```

peak_offpeak	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
cpp	.0064187	.0166063	0.39	0.699	-.0261366	.0389741
dap	.0415379	.0181648	2.29	0.022	.0059274	.0771484
ptr	.0131966	.0177959	0.74	0.458	-.0216907	.0480839
tou	-.011124	.0175354	-0.63	0.526	-.0455007	.0232527
bihd	.0017793	.0123469	0.14	0.885	-.0224258	.0259843
aihd	.0108243	.0135199	0.80	0.423	-.0156803	.0373289
pct	-.0124286	.017335	-0.72	0.473	-.0464124	.0215552

```
    bill_prot |   .0344527   .0217112     1.59   0.113    -.0081103    .0770158
   purch_tech |   .0034325   .0199408     0.17   0.863    -.0356598    .0425248
 notify_share |   .0182325   .0117666     1.55   0.121    -.0048349       .0413
    full_educ |  -.0183506   .0304894    -0.60   0.547    -.0781225    .0414214
         SFSH |   .0741587   .0738788     1.00   0.316    -.0706745    .2189918
         MFNS |  -.1757034   .0091048   -19.30   0.000    -.1935527   -.1578542
         MFSH |   -.103983   .0318169    -3.27   0.001    -.1663574   -.0416087
        _cons |   1.159235   .0242008    47.90   0.000     1.111791    1.206679
------------------------------------------------------------------------------
```

Table D-22 Impact of Multiple Notification Methods on Usage and

Table D-23 Impact of Multiple Notification Methods on Peak to Off-Peak Usage Ratios

Tables D-21 and D-22 contain results for four models detailed below. Each model contains one observation per customer; and customers are excluded if they are in treatment cells F1 or F2, are in any of the IBR treatment cells, or are screened due to data problems discussed in the report. The control group consists of customers in treatment cell F3 residing in single-family homes with non-space heating.

- Linear regression model using robust standard errors where the dependent variable is `usage`.

```
                                                       Number of obs =    5262
                                                       F( 15,  5246) =  109.26
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.1978
                                                       Root MSE      =  .73619

------------------------------------------------------------------------------
             |               Robust
       usage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         cpp |   .0077892   .0395889     0.20   0.844    -.0698216       .0854
         dap |   .0498468   .0429791     1.16   0.246    -.0344101    .1341038
         ptr |   .0116552   .0427086     0.27   0.785    -.0720714    .0953818
         tou |   .0540373   .0431609     1.25   0.211    -.0305761    .1386506
        bihd |  -.0197953    .027217    -0.73   0.467    -.0731519    .0335613
        aihd |   .0290439   .0315515     0.92   0.357    -.0328101     .090898
         pct |   .0129891   .0391948     0.33   0.740    -.0638491    .0898273
   bill_prot |   .0235404   .0480056     0.49   0.624    -.0705705    .1176514
  purch_tech |  -.0585772   .0483666    -1.21   0.226    -.1533959    .0362415
notify_share |   .1406877   .0261393     5.38   0.000     .0894437    .1919317
     methods |   .0015737   .0262762     0.06   0.952    -.0499386     .053086
   full_educ |  -.1655008   .0666914    -2.48   0.013    -.2962437   -.0347578
        SFSH |   .0439835    .193053     0.23   0.820    -.3344807    .4224477
        MFNS |  -.7415067   .0186185   -39.83   0.000    -.7780067   -.7050068
        MFSH |  -.6884632   .0795722    -8.65   0.000    -.8444579   -.5324685
       _cons |   1.502307   .0532922    28.19   0.000     1.397832    1.606782
------------------------------------------------------------------------------
```

- Linear regression model using robust standard errors where the dependent variable is `peak`.

```
                                                       Number of obs =    5262
                                                       F( 15,  5246) =  120.40
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.2096
                                                       Root MSE      =  .92635

------------------------------------------------------------------------------
             |               Robust
        peak |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
```

cpp	.0404277	.0461179	0.88	0.381	-.0499825	.130838
dap	.1147648	.0519793	2.21	0.027	.0128637	.2166659
ptr	.047578	.0507416	0.94	0.348	-.0518966	.1470527
tou	.0657775	.0510816	1.29	0.198	-.0343638	.1659188
bihd	-.0188359	.0348473	-0.54	0.589	-.0871512	.0494794
aihd	.0386662	.039098	0.99	0.323	-.0379822	.1153145
pct	-.0177796	.0471365	-0.38	0.706	-.1101866	.0746275
bill_prot	.0433337	.0625394	0.69	0.488	-.0792697	.165937
purch_tech	-.0561804	.0619672	-0.91	0.365	-.177662	.0653011
notify_share	.1777729	.032482	5.47	0.000	.1140947	.2414511
methods	-.0036516	.0331008	-0.11	0.912	-.068543	.0612398
full_educ	-.2293161	.0825614	-2.78	0.005	-.3911709	-.0674614
SFSH	.1167612	.2543995	0.46	0.646	-.3819676	.6154901
MFNS	-.9664237	.0232196	-41.62	0.000	-1.011944	-.9209035
MFSH	-.9246121	.054184	-17.06	0.000	-1.030835	-.8183889
_cons	1.726429	.0670399	25.75	0.000	1.595003	1.857855

- Linear regression model using robust standard errors where the dependent variable is `event_peak`.

Number of obs = 5262
F(15, 5246) = 124.52
Prob > F = 0.0000
R-squared = 0.2167
Root MSE = 1.2378

event_peak	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
cpp	-.0289768	.0623145	-0.47	0.642	-.1511391	.0931854
dap	.1043653	.0697699	1.50	0.135	-.0324126	.2411433
ptr	.016766	.0685122	0.24	0.807	-.1175465	.1510784
tou	.0534593	.0693778	0.77	0.441	-.08255	.1894687
bihd	-.0131877	.0459329	-0.29	0.774	-.1032352	.0768599
aihd	.0659637	.0520394	1.27	0.205	-.0360553	.1679827
pct	-.0199808	.0629547	-0.32	0.751	-.1433983	.1034367
bill_prot	.0648074	.0832118	0.78	0.436	-.0983224	.2279372
purch_tech	-.086568	.0802008	-1.08	0.280	-.2437949	.0706588
notify_share	.2544098	.0433051	5.87	0.000	.1695137	.3393059
methods	-.0208796	.0440357	-0.47	0.635	-.1072079	.0654488
full_educ	-.393795	.1176889	-3.35	0.001	-.6245142	-.1630757
SFSH	-.1014334	.3094303	-0.33	0.743	-.7080457	.5051788
MFNS	-1.313469	.0310202	-42.34	0.000	-1.374282	-1.252657
MFSH	-1.27743	.0716791	-17.82	0.000	-1.417951	-1.136909
_cons	2.38892	.0988131	24.18	0.000	2.195206	2.582635

- Linear regression model using robust standard errors where the dependent variable is `peak_offpeak`.

Number of obs = 5262
F(15, 5246) = 27.83
Prob > F = 0.0000
R-squared = 0.0691
Root MSE = .31926

peak_offpeak	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
cpp	.0066904	.0165926	0.40	0.687	-.0258381	.0392188

dap	.0415911	.0181645	2.29	0.022	.0059811	.0772012
ptr	.0132391	.0177947	0.74	0.457	-.0216459	.0481241
tou	-.0109504	.0175375	-0.62	0.532	-.0453312	.0234304
bihd	.0018632	.0123495	0.15	0.880	-.022347	.0260734
aihd	.0106407	.0135549	0.79	0.432	-.0159325	.037214
pct	-.0125578	.017337	-0.72	0.469	-.0465454	.0214299
bill_prot	.0343349	.0217048	1.58	0.114	-.0082156	.0768853
purch_tech	.0031208	.0199623	0.16	0.876	-.0360137	.0422553
notify_share	.019226	.0120236	1.60	0.110	-.0043453	.0427972
methods	-.0049089	.0110004	-0.45	0.655	-.0264742	.0166563
full_educ	-.018117	.0305033	-0.59	0.553	-.0779161	.0416821
SFSH	.0741477	.0739038	1.00	0.316	-.0707346	.2190299
MFNS	-.1757448	.0091018	-19.31	0.000	-.1935882	-.1579014
MFSH	-.1038749	.0318548	-3.26	0.001	-.1663236	-.0414263
_cons	1.159245	.0242028	47.90	0.000	1.111797	1.206692

Table D-24 Impact of Customer Contacts on Usage and

Table D-25 Impact of Customer Contacts on Peak to Off-Peak Usage Ratios

Tables D-24 and D-25 contain results for four models detailed below. Each model contains one observation per customer; and customers are excluded if they are in treatment cells F1 or F2, are in any of the IBR treatment cells, or are screened due to data problems discussed in the report. The control group consists of customers in treatment cell F3 residing in single-family homes with non-space heating.

- Linear regression model using robust standard errors where the dependent variable is `usage`.

```
Number of obs =    5262
F( 14,  5247) =  116.35
Prob > F      =  0.0000
R-squared     =  0.1942
Root MSE      =  .73774
```

usage	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
cpp	.0061581	.0396165	0.16	0.876	-.0715068	.083823
dap	.0472279	.0430192	1.10	0.272	-.0371075	.1315634
ptr	.0087728	.0428345	0.20	0.838	-.0752006	.0927462
tou	.0484447	.0432689	1.12	0.263	-.0363804	.1332698
bihd	-.0339773	.0288955	-1.18	0.240	-.0906246	.0226699
aihd	.0243687	.032103	0.76	0.448	-.0385666	.087304
pct	.0043183	.0395765	0.11	0.913	-.0732681	.0819046
bill_prot	.0274826	.0482237	0.57	0.569	-.067056	.1220212
purch_tech	-.0437333	.0489901	-0.89	0.372	-.1397742	.0523076
anycontact	.0508456	.0260264	1.95	0.051	-.0001769	.1018682
full_educ	-.0596323	.0648448	-0.92	0.358	-.1867551	.0674906
SFSH	.0622073	.1936978	0.32	0.748	-.3175209	.4419356
MFNS	-.7406703	.0187921	-39.41	0.000	-.7775107	-.7038299
MFSH	-.6980736	.0797601	-8.75	0.000	-.8544366	-.5417106
_cons	1.500879	.0532907	28.16	0.000	1.396407	1.605351

- Linear regression model using robust standard errors where the dependent variable is `peak`.

```
Number of obs =    5262
F( 14,  5247) =  128.11
```

```
                                                      Prob > F      =  0.0000
                                                      R-squared     =  0.2058
                                                      Root MSE      =  .92852

------------------------------------------------------------------------------
             |               Robust
        peak |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         cpp |   .0402799   .0462588     0.87   0.384    -.0504067    .1309665
         dap |   .1128484   .0520606     2.17   0.030     .0107881    .2149088
         ptr |   .0449327   .0509814     0.88   0.378    -.0550121    .1448775
         tou |   .0609799   .0513006     1.19   0.235    -.0395907    .1615504
        bihd |  -.0279909   .0366433    -0.76   0.445     -.099827    .0438452
        aihd |   .0372262   .0396058     0.94   0.347    -.0404177      .11487
         pct |  -.0239234   .0472652    -0.51   0.613    -.1165828     .068736
   bill_prot |   .0487743   .0627428     0.78   0.437    -.0742277    .1717762
  purch_tech |   -.043942   .0628034    -0.70   0.484    -.1670628    .0791788
  anycontact |   .0379772   .0330724     1.15   0.251    -.0268586    .1028129
   full_educ |   -.097318   .0799647    -1.22   0.224     -.254082    .0594461
        SFSH |   .1406191   .2557951     0.55   0.583    -.3608458     .642084
        MFNS |  -.9669215   .0234347   -41.26   0.000    -1.012863   -.9209798
        MFSH |   -.936173   .0545526   -17.16   0.000    -1.043119   -.8292273
       _cons |   1.725832   .0670747    25.73   0.000     1.594337    1.857326
------------------------------------------------------------------------------
```

- Linear regression model using robust standard errors where the dependent variable is `event_peak`.

```
                                                      Number of obs =    5262
                                                      F( 14,  5247) =  132.23
                                                      Prob > F      =  0.0000
                                                      R-squared     =  0.2124
                                                      Root MSE      =   1.241

------------------------------------------------------------------------------
             |               Robust
  event_peak |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         cpp |  -.0305083   .0625119    -0.49   0.626    -.1530577    .0920411
         dap |   .1011933   .0698711     1.45   0.148    -.0357831    .2381697
         ptr |   .0126821   .0688549     0.18   0.854    -.1223021    .1476664
         tou |   .0456273   .0695788     0.66   0.512    -.0907761    .1820307
        bihd |   -.028185   .0484175    -0.58   0.561    -.1231035    .0667334
        aihd |   .0636528   .0525778     1.21   0.226    -.0394216    .1667271
         pct |  -.0291903   .0631499    -0.46   0.644    -.1529904    .0946098
   bill_prot |   .0728007   .0834514     0.87   0.383    -.0907988    .2364002
  purch_tech |  -.0668915   .0811606    -0.82   0.410    -.2260001    .0922172
  anycontact |   .0589634   .0446827     1.32   0.187    -.0286334    .1465602
   full_educ |  -.2078694   .1142719    -1.82   0.069    -.4318898     .016151
        SFSH |  -.0678799   .3107277    -0.22   0.827    -.6770355    .5412757
        MFNS |  -1.313714    .031296   -41.98   0.000    -1.375067    -1.25236
        MFSH |  -1.294243   .0718246   -18.02   0.000    -1.435049   -1.153437
       _cons |   2.387798   .0988553    24.15   0.000        2.194    2.581595
------------------------------------------------------------------------------
```

- Linear regression model using robust standard errors where the dependent variable is `peak_offpeak`.

```
                                                      Number of obs =    5262
                                                      F( 14,  5247) =   29.28
                                                      Prob > F      =  0.0000
```

R-squared	= 0.0688
Root MSE	= .31928

peak_offpeak	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
cpp	.0077069	.0166567	0.46	0.644	-.0249471	.040361
dap	.0421756	.0181711	2.32	0.020	.0065526	.0777985
ptr	.0135203	.0178124	0.76	0.448	-.0213993	.04844
tou	-.0101996	.0175506	-0.58	0.561	-.044606	.0242069
bihd	.0059159	.0129546	0.46	0.648	-.0194805	.0313124
aihd	.0131091	.0136381	0.96	0.336	-.0136272	.0398455
pct	-.0104065	.0174619	-0.60	0.551	-.0446391	.0238261
bill_prot	.0352106	.0216995	1.62	0.105	-.0073295	.0777507
purch_tech	.0007509	.0201714	0.04	0.970	-.0387935	.0402953
anycontact	-.0110872	.0112716	-0.98	0.325	-.0331842	.0110099
full_educ	-.0051168	.029441	-0.17	0.862	-.0628334	.0525998
SFSH	.0771747	.073377	1.05	0.293	-.0666748	.2210243
MFNS	-.1766832	.0091638	-19.28	0.000	-.1946481	-.1587183
MFSH	-.1048006	.0317766	-3.30	0.001	-.167096	-.0425052
_cons	1.159874	.0241957	47.94	0.000	1.11244	1.207307

Table D-26 Impact of Rate and Technology on Number of Customer Contacts

Table D-26 contains the results of a Poisson regression model where the dependent variable is contacts. There is one observation per customer; and customers are excluded if they are in treatment cells F1 or F2 or are screened due to data problems discussed in the report. The control group consists of customers in treatment cell D1a residing in single-family homes with non-space heating.

	Number of obs	= 1329
	LR chi2(14)	= 68.06
	Prob > chi2	= 0.0000
Log likelihood = -2069.5204	Pseudo R2	= 0.0162

contacts	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
flr	-.0420764	.0866981	-0.49	0.627	-.2120016	.1278488
dap	-.0467177	.0736384	-0.63	0.526	-.1910464	.097611
ibr	-.1041445	.0818169	-1.27	0.203	-.2645026	.0562135
ptr	.026169	.0667091	0.39	0.695	-.1045784	.1569165
tou	.0695699	.0663568	1.05	0.294	-.0604871	.1996268
bihd	.2307608	.1108512	2.08	0.037	.0134965	.4480251
aihd	.5115018	.1147462	4.46	0.000	.2866034	.7364003
pct	.5385244	.1237004	4.35	0.000	.2960762	.7809726
bill_prot	-.0069575	.2106733	-0.03	0.974	-.4198695	.4059545
purch_tech	-.0605531	.1404052	-0.43	0.666	-.3357422	.214636
full_educ	-.0089232	.4280706	-0.02	0.983	-.8479263	.8300798
SFSH	.1643434	.3181787	0.52	0.605	-.4592754	.7879621
MFNS	-.0856126	.0485592	-1.76	0.078	-.180787	.0095618
MFSH	.17782	.1285948	1.38	0.167	-.0742213	.4298612
_cons	.2409444	.4175056	0.58	0.564	-.5773515	1.05924

Table D-27 Impact of Rate and Technology on Call Duration

Table D-27 contains the results of a linear regression model where the dependent variable is call duration. There is one observation per incoming call placed to the customer support center; and calls were excluded if they were placed by customers in treatment cells F1 or F2 or by customers screened due to data problems discussed in the report. The control group consists of customers in treatment cell D1a residing in single-family homes with non-space heating.

Number of obs =	1968
F(15, 1952) =	11.06
Prob > F =	0.0000
R-squared =	0.0100
Root MSE =	269.98

callduration	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
flr	-7.765869	26.5247	-0.29	0.770	-59.78559	44.25385
dap	-24.67802	18.8748	-1.31	0.191	-61.6949	12.33887
ibr	-33.32498	21.2541	-1.57	0.117	-75.0081	8.358142
ptr	-10.31434	21.13108	-0.49	0.626	-51.75621	31.12752
tou	-21.12653	18.66785	-1.13	0.258	-57.73753	15.48448
bihd	13.87135	39.66065	0.35	0.727	-63.91033	91.65304
aihd	-16.71325	41.19685	-0.41	0.685	-97.50768	64.08118
pct	-11.47664	45.46618	-0.25	0.801	-100.644	77.69072
bill_prot	-90.10049	52.85619	-1.70	0.088	-193.761	13.56001
purch_tech	-78.75474	30.93164	-2.55	0.011	-139.4173	-18.09222
full_educ	160.3214	45.92916	3.49	0.000	70.24604	250.3968
SFSH	90.31411	85.06205	1.06	0.288	-76.50789	257.1361
MFNS	-2.267379	13.92708	-0.16	0.871	-29.58088	25.04612
MFSH	36.30388	33.78978	1.07	0.283	-29.96396	102.5717
event	-32.94836	33.14707	-0.99	0.320	-97.95573	32.05901
_cons	176.1659	28.87536	6.10	0.000	119.5361	232.7957

Table D-28 Impact of Rate and Technology on Number of Customer Contacts

Table D-28 contains the results of a Poisson regression model where the dependent variable is contacts. There is one observation per customer, and customers are excluded if they are in treatment cells F1 or F2 or are screened due to data problems discussed in the report. The control group consists of customers in treatment cell F6 residing in single-family homes with non-space heating.

Number of obs =	1329
LR chi2(14) =	68.06
Prob > chi2 =	0.0000
Pseudo R2 =	0.0162

Log likelihood = -2069.5204

contacts	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
cpp	.0420764	.0866981	0.49	0.627	-.1278488	.2120016
dap	-.0046413	.0945901	-0.05	0.961	-.1900345	.1807519
ibr	-.0620681	.1009014	-0.62	0.538	-.2598313	.135695
ptr	.0682455	.0923492	0.74	0.460	-.1127555	.2492465
tou	.1116463	.0882983	1.26	0.206	-.0614153	.2847078

eweb	-.2307608	.1108512	-2.08	0.037	-.4480251	-.0134965
aihd	.2807411	.0525338	5.34	0.000	.1777768	.3837054
pct	.3077636	.0734063	4.19	0.000	.1638898	.4516374
bill_prot	-.0069575	.2106733	-0.03	0.974	-.4198695	.4059545
purch_tech	-.0605531	.1404052	-0.43	0.666	-.3357422	.214636
full_educ	-.0089232	.4280706	-0.02	0.983	-.8479263	.8300798
SFSH	.1643434	.3181787	0.52	0.605	-.4592754	.7879621
MFNS	-.0856126	.0485592	-1.76	0.078	-.180787	.0095618
MFSH	.17782	.1285948	1.38	0.167	-.0742213	.4298612
_cons	.4296287	.4231185	1.02	0.310	-.3996683	1.258926

Table D-29 Impact of Rate and Technology on Call Duration

Table D-29 contains the results of a linear regression model where the dependent variable is call duration. There is one observation per incoming call placed to the customer support center; and calls were excluded if they were placed by customers in treatment cells F1 or F2 or by customers screened due to data problems discussed in the report. The control group consists of customers in treatment cell F6 residing in single-family homes with non-space heating.

```
                                                  Number of obs =    1968
                                                  F( 15,  1952) =   11.06
                                                  Prob > F      =  0.0000
                                                  R-squared     =  0.0100
                                                  Root MSE      =  269.98
```

callduration	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
cpp	7.765869	26.5247	0.29	0.770	-44.25385	59.78559
dap	-16.91215	26.9597	-0.63	0.531	-69.78498	35.96069
ibr	-25.55911	28.4391	-0.90	0.369	-81.33331	30.21509
ptr	-2.548476	29.06572	-0.09	0.930	-59.55159	54.45464
tou	-13.36066	26.47216	-0.50	0.614	-65.27732	38.55601
eweb	-13.87135	39.66065	-0.35	0.727	-91.65304	63.91033
aihd	-30.5846	15.1522	-2.02	0.044	-60.30079	-.8684217
pct	-25.34799	23.84276	-1.06	0.288	-72.10793	21.41194
bill_prot	-90.10049	52.85619	-1.70	0.088	-193.761	13.56001
purch_tech	-78.75474	30.93164	-2.55	0.011	-139.4173	-18.09222
full_educ	160.3214	45.92916	3.49	0.000	70.24604	250.3968
SFSH	90.31411	85.06205	1.06	0.288	-76.50789	257.1361
MFNS	-2.267379	13.92708	-0.16	0.871	-29.58088	25.04612
MFSH	36.30388	33.78978	1.07	0.283	-29.96396	102.5717
event	-32.94836	33.14707	-0.99	0.320	-97.95573	32.05901
_cons	182.2714	41.26977	4.42	0.000	101.3339	263.2088

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